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# Decisions under risk programming with economic applications

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DECISIONS UNDER RISK PROGRAMMING WITH  
ECONOMIC APPLICATIONS

by

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A Dissertation Submitted to the  
Graduate Faculty in Partial Fulfillment of  
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1969

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## 1. INTRODUCTION

Mathematical programming (145, 61) is concerned with the problem of maximizing or minimizing a function of variables that are restricted by a number of constraints. Interest in this problem arose in economics and management sciences, where it was realized that many problems of optimum allocation of scarce resources could be formulated mathematically as programming problems. The introduction of large light-spaced electronic computers, moreover, made it possible in principle to obtain numerical solutions, provided efficient mathematical methods and computational techniques could be developed.

The concept of risk has played a very significant role in the theory of production, resource allocation, and the theory of statistical decisions. This is used here for analyzing the implications of a certain type of probabilistic programming models in a linear and non-linear framework. The plan of the discussion covering this topic will be as follows.

In Chapter 2 a general survey of risk programming is presented; the various methods of risk programming discussed in those sections are limited mostly to probabilistic linear programming of static variety, under simplifying assumptions regarding the statistical distributions of the parameters of the problems which are  $(A, b, c)$ . This is followed by Chapter

3 which presents the optimization techniques used in this thesis in order to deal with nonlinear deterministic forms produced by the risk programming problems. Here we are using the most powerful numerical techniques which enable us to solve problems that were impossible to solve in the past. Chapter 4 examined an empirical model of production planning and the emphasis here is on evaluating a reliability level for every period of production planning and comparing with chance constrained programming. We also considered an investment situation, where an investor wished to select a portfolio; this original model first formulated by Näslund (90, 89) is solved here in the general nonlinear fashion, extended to the nonlinear reliability programming case and analyzed in its sample distribution aspects. In Chapter 5 we indicated two applications of geometric programming to economic models, in the first case we use generalized polynomial programming applied to the simple stochastic production model, in the second case we applied geometric programming to the posynomials arising in Uzawa's model of economic growth (135).

Finally, a broad summary of all principal results and ideas for future research is presented in Chapter 6.



## 2. REVIEW OF LITERATURE IN RISK PROGRAMMING

Since the origin of the species, men have been making decisions, and experts have been telling them how they make, or should make decisions. Von Neumann and Morgenstern (91) developed a theory of maximizing the expected utility. In order for their results to be valid, however, their assumption that rational individuals are choosing the right utility function must hold true.

The fundamental problem of production is the optimum allocation of scarce resources between alternative ways of achieving an objective. It can be seen that the objective may be the maximization of the firm's profit or the minimization of costs. Cases exist, however, in which besides profit maximization or cost minimization, the objectives include risk minimization. If the decision-maker is willing to sacrifice profit in exchange for security, the result depends on his behavior.

The difference between uncertainty and risk must be pointed out here. Each term has had distinct meaning in different parts of economic literature. The term "risk" is characterized in a model in which the entire probability distribution of the outcomes has formally been taken into account, whether the character of that distribution is considered subjective or objective. The term "uncertainty" is

applied to models in which the above stated conditions are not the case.

It is very important to have a realistic theory explaining how individuals choose among alternate courses of action when the consequences of their actions are not fully known to them. A survey of the literature of approaches to the theory of choices in risk taking situations has been given by Arrow (3).

The probability theory represents the sustained efforts of mathematicians and philosophers to provide a rational basis on which expectations may be derived from past events. Roy (102) stated that there are major objections when one attempts to maximize expected gain or profit. The ordinary man has to consider the possible outcomes of a given course of action on one occasion only, and the average or expected outcome, if this conduct were repeated a large number of times under similar conditions, is irrelevant. Also, the well-known phenomenon of the diversification of resources among a wide range of project or investment situations is not explained.

Mathematical programming under risk has been developed during the last ten years and there exist many published articles in the field. The research, to date, can be divided in three major areas (88) namely:

- a) stochastic linear programming
- b) linear programming under uncertainty

c) chance constrained programming

All methods start from the linear programming formulation namely minimizing or maximizing a linear function subject to linear constraints. Stochastic linear programming is mainly concerned with studying the statistical distribution of  $\max z$ . This work has followed two lines namely the so called "passive" and "active" approaches. Programming under uncertainty partitions the problem into two or more stages. First the decision maker selects an initial decision, then the random effects occur. Chance-constrained programming allows for constraint violations a certain proportion of the time. Reliability programming is an extension of chance constrained programming where the probability levels are not preassigned, but optimized in some sense.

## 2.1. Stochastic Linear Programming

The ordinary linear programming problem can be formulated as follows (35, 57, 60)

$$\text{Max } c'x \quad [2.1.1]$$

subject to

$$\begin{aligned} Ax &\leq b \\ x &\geq 0 \end{aligned} \quad [2.1.2]$$

where

$c$  is a row vector with  $n$  elements

$x$  is a column vector with  $n$  elements

$A$  is a  $m$  by  $n$  matrix

$b$  is a column vector with  $m$  elements.

The problem is to find values for the elements of  $x$  which maximize [2.1.1] and satisfy [2.1.2]. Risk is introduced to the problem when either some elements of  $c$ ,  $A$  or  $b$  or any combination of them include random elements.

Stochastic linear programming which was first suggested by Tintner (130) is primarily concerned with the statistical distribution of  $\max z = c'x$  in [2.1.1]. It is assumed that a multivariate probability distribution for the elements of  $A$ ,  $b$ ,  $c$  in [2.1.1] and [2.1.2] is known. We may be represented, for instance, as

$$\text{Prob } (A, b, c) \quad [2.1.3]$$

where Prob refers to the probability of simultaneous occurrence of specified values of the matrix  $A$  and the vectors  $b$  and  $c$ .

Thus, given a Prob function as in [2.1.3] one may ask how  $\max c'x$  will be distributed. There are three types of distribution problems: the passive approach, active approach, termed distribution problems and expected values problems by

Vajda (136), and other distributional approaches.

The passive approach assumes that for each possible configuration of the random variables the optimal activities,  $x^0$  are selected. Then it is possible, at least in principle, to derive the probability distribution

$$F(z) \qquad \qquad \qquad [2.1.4]$$

of the linear form  $z$  to be optimized. To simplify the problem usually only the linear terms of the Taylor development of the function are retained. This is based on the assumption that the coefficients are independent. A confidence interval for the expected value of the function can be calculated (86, 84). This method has been developed by Babbar (6), Tintner (129) and extended by Sengupta (122, 109), Bereanu (13), Prekopa (99) and others (121). For example one way of obtaining a distribution of  $\max c'x$  that has been used (27) is to use a Monte Carlo routine to generate the values of the components of  $b$  based upon the given statistical distribution of  $b$ . When a set of values for  $b$  is selected the values of  $x$  can be solved using regular linear programming methods.

The active approach consists of transforming the problem into a decision problem. The problem can be reformulated in the following manner

$$\text{Max } c'x$$

subject to

$$Ax \leq bU$$

$$x \geq 0$$

where  $U$  is matrix with elements such that

$$0 \leq \mu_{ij} \leq 1 \quad i=1,2,\dots,m \quad j=1,\dots,n$$

and

$$\sum_{j=1}^n \mu_{ij} = 1$$

$U$  is a matrix of decision variables,  $\mu_{ij}$ , which denote the proportion of the resources  $i$  devoted to activity  $j$ . This also assumes that all resources are completely utilized.

In order to illustrate the method further we turn to the following example given in (88, 85) about an application to Iowa agriculture, the data are mentioned in detail by Babbar (6, 7). For other examples see (120, 108).

A farm that can either grow corn in amount  $x_1$  or raise flax in amount  $x_2$ . The net price of corn is 1.56 and the net price of flax is 3.81. There are two production factors namely land 148 units and capital 1800 units,  $a_{11}$  and  $a_{12}$  indicate the amount of land used for producing one unit of  $x_1$  and  $x_2$  respectively.  $a_{21}$  and  $a_{22}$  indicate the amount of capital used for producing one unit of  $x_1$  and  $x_2$  respectively.

The passive problem would have us find the probability distribution of  $\max z$

$$z \equiv 1.56 x_1 + 3.81 x_2$$

subject to

$$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \leq \begin{bmatrix} 148 \\ 1800 \end{bmatrix} \quad [2.1.5]$$

when the probability distribution of

$$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \quad \text{is specified.}$$

The active approach replaces the constraint [2.1.5] with

$$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_1 & 0 \\ 0 & x_2 \end{bmatrix} \leq \begin{bmatrix} 148 & 0 \\ 0 & 1800 \end{bmatrix} \begin{bmatrix} \mu_{11} & \mu_{12} \\ \mu_{21} & \mu_{22} \end{bmatrix}$$

and then proceeds to examine the distribution of  $\max z$  for various  $\mu_{ij} \geq 0$  allocations which satisfy

$$\mu_{11} + \mu_{12} = 1$$

$$\mu_{21} + \mu_{22} = 1$$

The objective is to choose a best set of  $\mu_{ij}$  values for the matrix  $u$  as judged relative to a suitable defined preference functional. The method has been applied in (25, 132).

The other distributional approaches (120) have been

concerned with several specific aspects of the general problem of which the following may be mentioned.

- (a) The extreme value aspects according to which each  $c_j$  coefficient of the objective function is replaced over the sample values ( $t=1,2,\dots,N$ ) by  $(\max_t c_{jt})$  or  $(\min_t c_{jt})$  and the resulting distribution of the optimal solution and its effects on the optimal decision role are analyzed (106, 105).
- (b) The implication of any departure from the assumption of normality, mutual independence and other simplifying conditions for the random elements of the problem; particularly the results which are relatively distribution-free are much needed (110).
- (c) The distribution of basic feasible solutions other than the optimal one (111) and the distribution of the posterior distribution of optimal profit, when the prior probabilities on  $c_j$  coefficients are replaced by the decision-maker by posterior probabilities through sampling experiments with consequent change in the optimal solution (116).
- (d) Distribution of the utility function  $u(z)$  of certain form, defined on set of values of the objective function  $z = c'x$  subject to the usual linear restrictions (18, 11).



Finally we review the earliest problem of the passive approach (114) in which the optimal basis equations are written as

$$(A+\alpha)x = (b+\beta) \quad [2.1.6]$$

where  $A$  and  $\alpha$  are  $m \times m$  matrices and  $x$ ,  $b$  and  $\beta$  are  $m \times 1$  vectors and where the random errors  $\alpha_{ij}$  and  $\beta_i$  are assumed to satisfy the following conditions

$$E(\alpha_{ij}) = E(\beta_i) = 0; \quad E\alpha_{ij}^2 = \sigma_{ij}^2 < \infty; \quad E\beta_i^2 = t_i^2$$

From [2.1.6] the  $k$ th optimal activity  $x_k$  can be solved for as

$$x_k = \frac{|D^k + d^k|}{|A + \alpha|} \quad k=1, \dots, m$$

where  $|D^k + d^k|$  is the determinant of matrix  $(A + \alpha)$  when its  $k$ th column is replaced by the column vector  $(b + \beta)$ .

We have also

$$z = \sum_{r=1}^m (c_r + \gamma_r) x_r$$

where

$$E\gamma_r = 0; \quad E\gamma_r^2 = w_r^2 < \infty$$

and the index set  $r=1, 2, \dots, m$  is defined for the optimal basic activities only.

If we are now limiting to first order errors and neglecting cross product terms of unlike random elements, the following expressions can be derived:

$$|D^k + d^k| \doteq |D^k| + \sum_{i=1}^m s_{ik} \beta_i + \sum_{i=1}^m \sum_{\substack{j=1 \\ j \neq k}}^m \alpha_{ij}^k \alpha_{ij} = N(x_k)$$

$$|A + \alpha| \doteq |A| + \sum_i \sum_j s_{ij} \alpha_{ij} = D(x)$$

$$\sum_{r=1}^m (c_r + \gamma_r) |D^r + d^r| = \sum_r c_r |D^r| + \sum_r c_r (\sum_i s_{ir} \beta_i)$$

$$+ \sum_{\substack{j=1 \\ j \neq r}}^m c_r \sum_i d_{ij}^r \alpha_{ij} + \sum_r |D^r| \gamma_r = N(z)$$

and

$$E|D^k + d^k| = |D^k| = d_k$$

$$\text{Var}|D^k + d^k| = \sum_i s_{ik}^2 t_i^2 + \sum_i \sum_j (d_{ij}^k)^2 \sigma_{ij}^2 = \sigma_k^2$$

$$E|A + \alpha| = |A| = a_0$$

$$\text{Var}|A + \alpha| = \sum_i \sum_j s_{ij}^2 \sigma_{ij}^2 = \sigma_A^2$$

$$\text{Cov}(|D^k + d^k|, |A + \alpha|) = \sum_i \sum_j d_{ij}^k s_{ij} \sigma_{ij}^2 = \sigma_{Ak}^2$$

$$E[N(z)] = \sum_r |D^r| c_r = d_{N(z)}$$

$$\text{Var } N(z) = \sum_{r=1}^m \left( \sum_{i=1}^m c_i s_{ri} \right)^2 t_r^2 + \sum_{r=1}^m c_r^2 \left[ \sum_{i=1}^m \sum_{\substack{j=1 \\ j \neq r}}^m (d_{ij}^r)^2 \sigma_{ij}^2 \right]$$

$$+ \sum_r |D^r|^2 w_r^2 = \sigma_{N(z)}^2$$

$$z = N(z) |D(z) \quad \text{where} \quad |A + \alpha| = D(x) = D(z)$$

with

$$E[D(z)] = |A| = a_0; \quad \text{Var } D(z) = \sigma_A^2 \text{ and}$$

$$\text{Cov}[N(z), D(z)] = \sum_r c_r \sum_{\substack{i,j \\ j \neq r}} d_{ij}^r s_{ij} \sigma_{ij}^2 = \sigma_{A.N(z)}^2$$

where  $s_{ik}$  is the cofactor of element  $a_{ik}$  in  $|A|$  and  $d_{ij}^k$  is the cofactor of the element  $D_{ij}$  in  $|D^k|$  and  $|D^k|$  is the determinant of  $A$  with its  $k$ th column replaced by the resource vector  $b$ .

It is observed that since  $N(x_k)$ ,  $D(x_k)$ ,  $N(z)$ ,  $D(z)$  are linear functions of normally distributed variables, they themselves will be normally distributed, and the problem becomes one of finding the distribution of the ratios

$$x_k = \frac{N(x_k)}{D(x_k)} \quad \text{and} \quad z = \frac{N(z)}{D(z)}$$

Using the result due to Geary (59), it is shown by Babbar and Tintner (7, 129) that the probability density of  $z$  for example is given by

$$f(z) = \frac{1}{\sqrt{2\pi}} \frac{[\bar{D}\sigma_N^2 - \bar{N}\sigma_{ND} + z(\bar{N}\sigma_D^2 - \bar{D}\sigma_{ND})]}{[\sigma_D^2 z^2 - 2z\sigma_{ND} + \sigma_N^2]^{3/2}}.$$

$$\exp \left[ -\frac{1}{2} \left\{ \frac{(D_z - \bar{N})^2}{\sigma_D^2 z^2 - 2z\sigma_{ND} + \sigma_N^2} \right\} \right]$$

where  $\bar{N}$  and  $D$  are two normally distributed variables with means  $\bar{N}$ ,  $\bar{D}$  and covariance  $\sigma_N^2$ ,  $\sigma_D^2$ ,  $\sigma_{\bar{N}D}$ .

Babbar (7) then discusses confidence intervals for the ratios, cumulative distributions, etc. and closes with a numerical application of these techniques to linear programming. Extension of this problem has been developed in (118, 119, 117).

## 2.2. Programming under Uncertainty

We have already pointed out the difference between uncertainty and risk since we are always going to use the name originally given to the method (36).

A class of linear programming models is considered where the activities are divided into two or more stages. The quantities of activities in the first stage are the only ones that can be determined in advance because those in the second and later stages depend on the outcome of random events.

Madansky (76) has classified the methods of reducing the effects of uncertainty in a linear programming problem into three types.

- (a) Replacing all random elements by their expected values the so-called expected value solution.
- (b) Replacing the random elements by pessimistic estimates of their values in the second stage one could compensate for the loss due to inaccuracies in the

first-stage decisions. The so-called fat solution.

- (c) Reducing the problem to a two stage or multistage problem, where in the second stage one could compensate for the loss due to inaccuracies in the first-stage decisions. The so-called slack solution.

Finally we formulate the general multi-stage problem given in Dantzig (36). The structure assumed is

[illegible]

where  $b_1$  is a known vector;  $b_i$  is a chance vector ( $i=2, \dots, m$ ) whose components are functions of a point  $E_i$  drawn from a multidimensional distribution;  $A_{ij}$  are known matrices. The sequence of decisions is as follows:  $x_1$  the vector of non-negative activity levels in the first stage, is chosen so as to satisfy the first stage restrictions  $b_1 = A_{11}x_1$ ; the values of components of  $b_2$  are chosen by chance by determining  $E_2$ ;  $x_2$  is chosen to satisfy the 2nd stage restrictions

$b_2 = A_{21}x_1 + A_{22}x_2$ , etc. iteratively for the third and higher stages. It is further assumed that

- (1) The components of  $x_j$  are non-negative;
- (2) There exists at least one  $x_j$  satisfying the  $j$ th stage restraints, whatever be the choice of  $x_1, x_2, \dots, x_{j-1}$  satisfying the earlier restraints or the outcomes  $b_1, b_2, \dots, b_m$ .
- (3) The total cost  $c$  is a convex function in  $x_1, x_2, \dots, x_m$  which depend on the value of the sample points  $E_2, E_3, \dots, E_m$ .

When the number of possibilities for the chance vector  $b_2$  is  $b_2^{(1)}, b_2^{(2)}, \dots, b_2^{(k)}$  with probabilities  $p_1, p_2, \dots, p_k$ , ( $\sum p_i = 1$ ), it is not difficult to obtain a direct linear programming solution for small  $k$ , say  $k=3$ . Since this type of structure is very special, it appears likely that techniques can be developed to handle large  $k$ . For  $k=3$ , the problem is equivalent to determining vectors  $x_1$  and vectors  $x_2^{(1)}, x_2^{(2)}, x_2^{(3)}$  such that

$$b_1 = A_{11}x_1$$

$$b_2^{(1)} = A_{21}x_1 + A_{22}x_2^{(1)}$$

$$b_2^{(2)} = A_{21}x_1 + A_{22}x_2^{(2)}$$

$$b_2^{(3)} = A_{21}x_1 + A_{22}x_2^{(3)}$$

$$\text{Min } E(c) = c_1 x_1 + p_1 c_2 x_2^{(1)} + p_2 c_2 x_2^{(2)} + p_3 c_3 x_2^{(3)}$$

where for simplicity we have assumed a linear objective function.

Application of this method and extension may be found in (10, 75, 76, 40, 46, 136, 12, 137, 74).

### 2.3. Chance-Constrained Programming<sup>1</sup>

A new conceptual and analytical vehicle for problems of temporal planning under uncertainty, involving determination of optimal (sequential) stochastic decision rules is defined by Charnes and Cooper (22).

The problem of stochastic (or better, chance-constrained) programming is defined as follows. Select certain random variables with known distributions in such a manner as (a) to maximize a functional of both classes of random variables subject to (b) constraints on these variables which must be maintained at prescribed levels of probability. More loosely, the problem is to determine optimal stochastic decision rules under these circumstances. An example is supplied in (26). Temporal planning in which uncertainty elements are present, but in which management has access to "control variables" with which to influence outcomes, is a general way of characterizing these problems. Thus, queuing problems in which the

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<sup>1</sup>This part is based on (100).

availability of servers, customers, or both are partly controllable fall within this classification. It should be noted that the constraints to be maintained at the specified levels of probability will typically be given in the form of inequalities.

Chance-constrained programming admits random data variations and permits constraint violations up to specified probability limits. Different kinds of decision rules and optimizing objectives may be used so that under certain conditions, a programming problem (not necessarily linear) can be achieved, that is deterministic in that all random elements have been eliminated. Existence of such "deterministic equivalent" in the form of specified convex programming problems is established for a general class of linear decision rules (24) under the following three classes of objectives: (1) maximum expected value ('E model'); (2) minimum variance ('V model') and (3) maximum probability ('P model').

A chance-constrained formulation would replace the ordinary linear programming problem with a problem of the following kind:

Optimize  $f(c,x)=\text{Max } c'x$

Subject to Prob  $(Ax \leq b) \geq \alpha, \quad x \geq 0$  [2.3.1]

A,b,c are not necessarily constant but have, in general,



some or all of their elements as random variables. The vector  $\alpha$  contains a prescribed set of constants that are probability measures of the extent to which constraint violations are admitted. Thus, an element  $0 \leq \alpha_i \leq 1$  is associated with a constraint  $\sum_{j=1}^n a_{ij} x_j \leq b_i$  to give

$$\text{Prob} \left( \sum_{j=1}^n a_{ij} x_j \leq b_i \right) \geq \alpha_i \quad [2.3.2]$$

a double inequality which is interpreted to mean that the  $i$ th constraint may be violated but at most  $\beta_i = 1 - \alpha_i$  proportion of the time.

Here it is proposed to examine important classes of chance-constrained problems and to obtain deterministic equivalents that are then known in certain cases to be convex programming problems. It is to be emphasized, however, that optimization under risk immediately raises very important questions concerning a choice of rational objectives. Questions can arise, for example, concerning the reasonableness of an expected value optimization. Without attempting to resolve these issues, it should be noted that the evaluators secured for one objective are not necessarily correct or optimal when applied to the same problem under an altered objective.

It is assumed that a choice of values for decision variables  $x$  will not disturb the densities associated with the

random variables in  $A, b, c$ . Then we may formulate the general problem in terms of choosing a suitable decision rule

$$x = \phi(A, b, c) \quad [2.3.3]$$

with the function  $\phi$ , to be chosen from a prescribed class of functions and applied in a manner that guarantees that  $x$  values, as generated, will satisfy the chance constraints of [2.3.1] and optimize  $f(c, x)$  in [2.3.1] with reference to the class of rules from which the  $\phi$  of [2.3.2] is to be chosen.

By assuming that the matrix  $A$  is constant (i.e. non-random)  $x$  will also be restricted by the rule [2.3.3] to members of the class

$$x = Db \quad [2.3.4]$$

where  $D$  is a  $n \times m$  matrix whose elements are to be determined by reference to [2.3.1].

We will examine all possible rules of form  $D$  and, for important classes of objective and statistical distributions, in order to be able to characterize situations in which a deterministic equivalent will be achieved-irrespective of the  $D$  choice thus yielding a convex programming problem.

The expected value model ('E model') is then

$$\begin{aligned} &\text{maximize} && E \ c' \ x \\ &\text{under conditions} && \text{Prob} (Ax \leq b) \geq \alpha \end{aligned} \quad [2.3.5]$$

substituting [2.3.4] into the objective function of [2.3.5] one obtains

$$E(c'Db) = (Ec)' D(Eb)$$

It will assume that  $b$  and  $c$  are uncorrelated, then it will define the vectors

$$\mu_c' \equiv (Ec)'; \quad \mu_b' \equiv (Eb)'$$

then

$$\text{Min} - \mu_c' D \mu_b$$

Denoting the  $i$ th row of the matrix  $A$  by  $a_i'$  and  $(b - \mu_b)$  by  $\hat{b}$  and assuming normality of distribution for the variates  $(a_i', D \hat{b} - \hat{b}_i)$ , parts of the constraints of [2.3.4] may be written as

$$\begin{aligned} \text{Prob } (a_i' Db - b_i \leq 0) &= \text{Prob } (b_i - a_i' Db \geq 0) \\ &= \text{Prob } (\hat{b}_i - a_i' D \hat{b} \geq \mu_{b_i} + a_i' D \mu_b) \geq \alpha_i \end{aligned}$$

Assuming  $E(\hat{b}_i - a_i' D \hat{b})^2 > 0$ , the above can be normalized and  $i$ th constraint can be written fully as

$$\text{Prob } \frac{b_i - a_i' D \hat{b}_i}{\sqrt{E(\hat{b}_i - a_i' D \hat{b})^2}} \geq \frac{-\mu_{b_i} + a_i' D \mu_b}{\sqrt{E(\hat{b}_i - a_i' D \hat{b})^2}} \geq \alpha_i \quad [2.3.6]$$

by the assumption of normality, the left-hand side of the argu-

ment, i.e.  $(\hat{b} - a_i' D \hat{b}_i) / \sqrt{E(\hat{b}_i - a_i' D \hat{b})^2}$  is a standardized normal variable with zero mean and unit variance, so that [2.3.6] is replaced by

$$F_i \frac{-\mu_{b_i} + a_i' D \mu_b}{\sqrt{E(\hat{b}_i - a_i' D \hat{b})^2}} \quad [2.3.7]$$

where

$$F_i(w) = (\sqrt{2\pi})^{-1} \int_w^\infty e^{-y^2/2} dy$$

Usually for normal distribution  $\alpha_i > 0.5$  is taken, then the equation [2.3.7] can be solved as

$$\frac{-\mu_{b_i} + a_i' D \mu_b}{\sqrt{E(\hat{b}_i - a_i' D \hat{b})^2}} \leq F_i^{-1}(\alpha_i) \equiv -q_i \quad [2.3.8]$$

where  $q_i > 0$  for all  $i$ , if  $\alpha_i > 0.5$ .

The system [2.3.8] which involves nonrandom variables (i.e.), deterministic values only can be further reduced to a convex programming problem by introducing new variable  $v_i$  and writing [2.3.8] as

$$-\mu_{b_i} + a_i' D \mu_b \leq -v_i \leq -q_i \sqrt{E(\hat{b}_i - a_i' D \hat{b})^2} \leq 0$$

or

$$\mu_{b_i} - a_i' D \mu_b \geq v_i \geq q_i \sqrt{E(\hat{b}_i - a_i' D \hat{b})^2} \geq 0$$

which can be further simplified by squaring both sides, since nonnegativity is assigned to all expressions between inequality signs i.e.,

$$\begin{aligned} -a_i' D \mu_b - v_i &\geq -\mu_{b_i} \\ -q_i^2 E(\hat{b}_i - a_i' D b)^2 + v_i^2 &\geq 0 \end{aligned}$$

with  $v_i \geq 0$  for each  $i$ . Hence, the equivalent convex program for chance-constrained programming [2.3.5] is

Minimize  $-\mu_c' D \mu_b$   
under the conditions

$$\mu_{b_i} - a_i' D \mu_b - v_i \geq 0 \quad [2.3.9]$$

$$-q_i^2 E(a_i' D b - b_i)^2 + q_i^2 (\mu_{b_i} - a_i' D \mu_b)^2 + v_i^2 \geq 0$$

where the problem [2.3.9] is a convex programming problem in the variables  $D$  and  $V$

For the minimum variance ('V model')

$$\text{Min } E(c'x - c^0, x^0)^2$$

under the conditions [2.3.10]

$$\text{Prob } (Ax \leq b) > \alpha$$

$$x = Db$$

where the objective is to minimize a generalized mean square error i.e., taking all relations between the  $c_j$  into account, it is intended to minimize this measure of their deviations

about some given preferred values  $z^0 = c^0, x^0$ .

It is easy to achieve the following deterministic equivalent to [2.3.10]

$$\text{Min } E(c'Db - c'x)^2$$

under conditions

$$\mu_{b_i} - a_i'D\mu_b - v_i \geq 0$$

$$-q_i^2 E(a_i'Db - b_i)^2 + q_i^2 (\mu_{b_i} - a_i'D\mu_b)^2 + v_i^2 \geq 0$$

$$v_i \geq 0$$

This deterministic equivalent is again a convex programming problem.

The maximum probability ('P model') turns to a version of the satisficing approach. In this approach the  $c^0, x^0$  components are specified relative to some set of values - e.g., as generated from an aspiration level mechanism - which an organization (an individual or a business firm in the present context) will regard as satisfactory whenever these levels are achieved. Of course, when confronting an environment subject to risk, the organization cannot be sure of achieving these levels when effecting its choice from what it believes are available alternatives. On the other hand, if it does not achieve the indicated  $c^0, x^0$  levels or, more precisely, if it believes that it cannot achieve them at a satisfactory level of probability, then the organization will either (a) reorient its activities and 'search' for a more favorable environment

or else (b) alter its aspirations and, possibly, the probability of achieving them.

The model is  $\text{Max Prob } (c'x \geq c^0, x^0)$

under the conditions

$$\text{Prob } (Ax \leq b) \geq \alpha \quad [2.3.11]$$

$$x = Db$$

If the same rules and assumptions are utilized as before to reduce this to a deterministic equivalent, it then becomes

$$\text{Max } v_0/w_0$$

under conditions

$$\mu_c' D \mu_b - v_0 \geq \mu_c^0 \quad [2.3.12]$$

$$- E(c'Db - c^0, x^0)^2 + w_0^2 \geq 0$$

$$\mu_{b_i} - a_i' D \mu_b - v_i \geq 0$$

$$-q_i^2 E(a_i'Db - b_i)^2 + q_i^2 (\mu_{b_i} - a_i' D \mu_b)^2 - v_i^2 \geq 0$$

$$v_i \geq 0$$

This problem can be solved using fractional programming methods; for more details see (22).

Sengupta (55) points out two aspects which may be noted about this method. The first aspect is that it characterizes the problem only within a very restricted class of decision rules, and the operational efficiency of the method must be

determined by further experimentation. In other words, one could specify other types of deterministic equivalents (11) which would subsume the cases considered here. Secondly, the decision rules here are not analytic, i.e., each time they have to be solved with the appearance of new data. An extension of this idea of deterministic equivalent in terms of recursive programming may be helpful, although it will involve nonlinear difference equations that are very difficult to solve.

Shinji Kataoka (71) introduced a new objective function, which is suitable for stochastic programming, utilizing Charnes' and Cooper's model. That is

$$\text{Max } f \quad [2.3.13]$$

Subject to

$$\text{Prob } (c'x \leq f) = \alpha \quad [2.3.14]$$

and

$$\text{Prob } (Ax \leq b) \geq \beta \quad [2.3.15]$$

$$x \geq 0$$

It should be noted that the expected value of profit is not always considered a good measure for the optimality criterion. Even though a policy  $x$  dominates other policies in the expectation of profit, it may be more risky in that the chance of getting a very low profit may be greater than for other policies because of the dispersion of its distribution.



For this reason, the lower allowable limit  $f$  defined by [2.3.14] a special form of [2.3.15] for a given probability  $\alpha$  is maximized instead of the expected value profit.

A case is considered in which the  $b_i$ 's and  $c_j$ 's are random variables, but the  $a_{ij}$ 's are constant. Transportation and production horizon problems belong to this category if customer demand and commodity price are random. This is called a transportation type problem.

Kataoka has made the following assumptions and formulations.

A.1. The random variable  $b_i$  has a normal distribution with mean value  $\bar{b}_i$  and variance  $\sigma_{b_i}^2$

The probability in [2.3.15] can be transformed as

$$\text{Prob} \left( \sum_j a_{ij} x_j \leq b_i \right) = \text{Prob} \left( \frac{b_i - \bar{b}_i}{\sigma_{b_i}} \geq \frac{\sum_j a_{ij} x_j - \bar{b}_i}{\sigma_{b_i}} \right)$$

then the left hand side of the argument is a normalized random variable with zero mean and unit variance. Hence the probability condition, [2.3.15] is replaced by

$$G \left( \frac{\sum_j a_{ij} x_j - \bar{b}_i}{\sigma_{b_i}} \right) \geq \beta_i$$

or

$$\sum_j a_{ij} x_j - \bar{b}_i \leq G^{-1}(\beta_i) = -q_i$$

where

$$G(x) = (\sqrt{2\pi})^{-1} \int_x^{\infty} e^{-y^2/2} dy$$

usually it is considered that  $\beta_i \geq 0.5$ ; then  $G^{-1}(\beta_i) \leq 0$ .

A.2. The vector  $c$  has a multinormal distribution with mean value vector  $\bar{c} = (c_1, c_2, \dots, c_n)$  and a dispersion matrix  $V$ . The variance of  $c'x$  is  $x'Vx$ . Hence

$$\text{Prob}(c'x \leq f) = \text{Prob} \left( \frac{c'x - \bar{c}'x}{\sqrt{x'Vx}} \leq \frac{f - \bar{c}'x}{\sqrt{x'Vx}} \right) = I \left( \frac{f - \bar{c}'x}{\sqrt{x'Vx}} \right)$$

where

$$I(x) = (\sqrt{2\pi})^{-1} \int_{-\infty}^x e^{-y^2/2} dy$$

then for (2.3.14) is

$$f = \bar{c}'x + I^{-1}(\alpha) \sqrt{x'Vx}$$

Finally Kataoka has a maximization problem

$$\text{Max } f_I = \bar{c}'x + I^{-1}(\alpha) \sqrt{x'Vx} \quad ; \quad [2.3.16]$$

under the conditions

$$Ax \leq \bar{b}_i + G^{-1}(\beta_i) \sigma_{b_i}$$

Kataoka also transforms a model to a more general stochastic programming problem in which the components of matrix  $A$  are random variables; for more details see (71).

Sengupta (107) considers three generalized standpoints. First, the assumption of normality is replaced by a chi-square distribution, which has a nonnegative range and hence more applicability to economic problems of production planning; and a confidence interval for the optimal solution vector is worked out on this basis. Second, the relevance of chance-constrained programming to sensitivity analysis of optimizing economic models is briefly indicated. Third, the applicability of chance-constrained decision rules to problems of development planning through investment programming is discussed.

Sengupta (107) assumes that the elements  $a_{ij}, b_i$ , of  $A$  and  $b$  respectively are taken to be mutually independent chi-square variates with means  $\bar{a}_{ij}$  and  $\bar{b}_i$  and these are denoted by  $\chi^2_{ij}(a_{ij})$  and  $\chi^2(b_i)$  respectively. He mentions two points about the reasonableness of this assumption. First, in most economic problems of production and resource allocation, the input coefficients  $a_{ij}$  represent coefficients of production function and therefore these must be nonnegative. Similarly, the resource vector must be nonnegative. Second, a chi-square, which is closely related to the normal (e.g., a normal variate truncated at  $y \geq 0$  results in a chi-square) has properties very similar to a normal distribution (e.g., reproductive properties) and hence approximations can easily be worked out by means of normal tables whenever needed.

In the derivation of his model, Sengupta assumes for a moment that  $b$  is not random. By transformation [2.3.1] becomes

$$\text{Prob}(\chi_i^2(\sum_{j=1}^n \bar{a}_{ij}) \leq \frac{b_i \sum_j \bar{a}_{ij} x_j}{\sum_j \bar{a}_{ij} x_j^2}) \geq \alpha_i \quad [2.3.17]$$

or, alternatively as,

$$F_i(b_i \sum_{j=1}^n \bar{a}_{ij} x_j / \sum_{j=1}^n \bar{a}_{ij} x_j^2) \geq \alpha_i \quad (i=1, \dots, n)$$

where  $f_i(w)$  is the cumulative distribution function of a central chi-square variate with degrees of freedom

$$N = \sum_j \bar{a}_{ij}, \text{ i.e.}$$

$$F_i(w) = (2^{N/2} \Gamma(N/2))^{-1} \int_0^w t^{(N/2)-1} \exp(-t/2) dt$$

Since the ordinary chi-square tables give the various significance points for  $w$  for a given degree of freedom, it would be possible to compare the exact values of

$$W = b_i \sum_{j=1}^n \bar{a}_{ij} x_j / \sum_{j=1}^n \bar{a}_{ij} x_j^2$$

satisfying the inequality [2.3.17]. For example, if  $d_i = .990$  (i.e., the tolerance measure) and  $\sum_j \bar{a}_{ij} = 7.0$ , then from the chi-square table one finds that

$$\text{Prob}(\chi_i^2(7.0) \leq w_0) = .990$$

implies a value of  $w_0 = 18.4753$ . Therefore, if it is taken

that  $w \geq w_0$ , this would satisfy a tolerance measure of 99% or higher. Since, for any preassigned value of tolerance measure  $\alpha_i$  and the value of  $N = \sum_j \bar{a}_{ij}$ , one can find a positive value of  $w_0$  from the chi-square table.

The chance-constrained programming model [1.2.1] then is finalized as a convex programming problem of the following type.

$$\text{Minimize } -c'x = - \sum_{j=1}^n c_j x_j$$

under the conditions

$$b_i \sum_{j=1}^n \bar{a}_{ij} x_j - q_i \sum_{j=1}^n \bar{a}_{ij} x_j^2 \geq 0$$

where

$$q_i = w_0 \quad x_j \geq 0$$

For a general case, Sengupta uses the F distribution when  $b$  is also random and he obtains the following concave programming problem.

$$\text{Maximize } c'x = \sum_{j=1}^n c_j x_j$$

under the restrictions

$$\bar{b}_i \left( \sum_{j=1}^n \bar{a}_{ij} x_j \right) - k_i \left( \sum_{j=1}^n \bar{a}_{ij} x_j^2 \right) \left( \sum_{j=1}^n \bar{a}_{ij} \right) \geq 0$$

$$\vdots$$

$$x_j \geq 0$$

where  $K_i$  is obtained as follows.

$$r = \left( \sum_{j=1}^n \bar{a}_{ij} x_j^2 \right) \left( \sum_j \bar{a}_{ij} \right) / \bar{b}_i \left( \sum_{j=1}^n a_{ij} x_j \right)$$

$$M_1 = \sum_{j=1}^n \bar{a}_{ij}; \quad M_2 = \bar{b}_i$$

therefore

$$\text{Prob } (F(M_1, M_2) \leq 1/r) \geq \alpha_i$$

then

$$K_1 = 1/r_0$$

Sengupta (107) considers that at the macroeconomic level, chance-constrained interpretations are most appropriate for the restrictions of a linear programming model applied to development planning. At the microeconomic level, the chance-constrained model is applicable most appropriately to situations of portfolio investment allocation and the holding of assets when a margin of safety is desired.

Further interesting results can be obtained assuming another kind of distribution with nonnegative range such as the exponential, the gamma or the beta distribution.

In the economic world disasters may occur. For a great many people, the idea of a disaster exists and the principle of "safety first" asserts that it is reasonable and probable

in practice that an individual will seek to reduce as far as possible the chance of a catastrophe occurring.

A single disaster is a discontinuity in one's pattern of behavior and in one's scale of preferences, viz. death, bankruptcy or a prison sentence.

A. D. Roy (102) has developed the safety first principle in terms of minimizing the upper bound of the chance of a dread event, where the information available about the joint probability distribution of future occurrences is confined to the first and the second order moments only.

From a formal standpoint, the minimization of the chance of a disaster can be interpreted as maximizing expected utility if the utility function assumes only two values, e.g. one if disaster does not occur, and zero if it does. It would appear that this formal analogy is scarcely helpful, since in the one case an individual is trying to make the expected proportion of occurrences of disaster as small as possible, while in maximizing expected utility he is operating at a different level of satisfaction.

A complete hypothesis about individual or corporate economic behavior under uncertainty must specify three things. It must describe the way in which expectations are formed from experience of the hard facts of life, the objectives which the entity under examination is trying to achieve, and the opportunities present for attaining such ends.

It may be possible that the outcome of economic activity which is regarded as disaster, is not independent of the expected value of the outcome. Thus, a person may be prepared to revise the level of disaster downwards if the expected return is at the same time raised. For example, he may at one and the same time regard a speculative loss of 10 percent as a disaster if the expected gain is only 5 percent, while, if the expected gain is 15 per cent, he will only get excited if his loss exceeds 25 per cent. Once again, such individual psychology can no doubt be interpreted in terms of utility function, but such development will not be pursued here. In the following discussion, the disaster level of the outcome is taken to be constant.

Let it be supposed, then, that the principle of safety first is adopted and that, when confronted with a range of possible actions, we are concerned that our gross return  $m$  should not be less than some quantity  $d$ . With every possible action, this outcome is not certain. There is coupled with  $m$  a quantity  $\sigma$  (the standard error of  $m$ ) which is, very roughly, the average amount by which the prediction  $m$  is expected to be wrong. In the following, it is assumed that  $m$  and  $\sigma$  are known precisely, whereas in fact they must be estimated from information about the past. This raises all kinds of problems, which are beyond the scope of this discussion, since estimates of  $m$  and  $\sigma$ , say  $\hat{m}$  and  $\hat{\sigma}$ , will themselves have sampling distributions.



Thus a full analysis of the problem should discuss simultaneously not only behavior under uncertainty but also actions under uncertain uncertainty.

In the particular application of the principle of safety first which is examined here, (102), it is postulated that  $m$  and  $\sigma$  are the quantities that can be distilled out of our knowledge of the past. The slightest acquaintance with problems of analyzing economic time series will suggest that this assumption is optimistic rather than unnecessarily restrictive.

Given the values of  $m$  and  $\sigma$  for all feasible choices of action, there will exist a functional relationship between these quantities, which will be denoted by  $F(\sigma, m) = 0$ . There may be a whole family of such relationships; in this case  $F(\sigma, m) = 0$  is their envelope. Since it is not possible to determine with this information the precise probability of the final return being  $d$  or less for a given pair of values of  $m$  and  $\sigma$ , the only alternative open is a calculation of the upper bound of this probability. This can be done by an appeal to the Bienaymé-Tchebycheff inequality. Thus, if the final return is a random variable  $z$  then

$$\text{Prob } (|z - m| \geq m - d) \leq \frac{\sigma^2}{(m - d)^2}$$

If, then, in default of minimizing  $P(z \leq d)$ , one operates on  $\sigma^2 / (m - d)^2$ , this is equivalent to maximizing  $(m - d) / \sigma$ .

Telser (128) postulates a particular attitude toward risk which stems from Roy's paper dealing with the theory of asset holding. He asks what assumptions make about entrepreneurial behavior in the face of uncertainty and whether or not entrepreneurs maximize their expected income. Suppose an entrepreneur wishes to select a portfolio of assets so as to maximize expected net income. Then he would buy only one asset, namely, that whose price is expected to increase the most. If he is right, he would gain a great deal, but conversely, if he is wrong he would lose a great deal. It has been observed that people diversify their portfolios, hence reject the hypothesis that entrepreneurs maximize expected net income.

However, entrepreneurs do prefer larger net incomes to smaller net incomes. Suppose an entrepreneur considers all his actions and strategies and for each action calculates the probability that the income resulting from the action, which is a random variable, falls short of a disaster level. For each action  $a$  there is a probability distribution of net income  $I$  which can be written  $\text{Prob}(I \leq c; a)$  where  $c$  is some constant. One computes the  $\text{Prob}(I \leq r; a)$  where  $0 \leq p \leq 1$ , and  $r$  is the disaster level of income. This disaster level of income,  $r$ , could be associated with bankruptcy or with something less dramatic.

Suppose that the entrepreneur does not want the

probability of his net income falling short of  $r$  to exceed  $\alpha$ . Hence he will not choose any action such that  $\text{Prob} (I \leq r; a) = p > \alpha$ . By this means, all his actions can be put into one of two classes. The first class consists of all the actions  $a$  such that  $\text{Prob} (I \leq r; a) > \alpha$  and the second class consists of all the actions  $a$  such that the  $\text{Prob} (I \leq r; a) \leq \alpha$ . All the actions in the second class shall be called admissible.

Then the entrepreneur will choose that action  $a$  of the admissible actions such that his expected income is at a maximum. Mathematically this means that the entrepreneur chooses the action  $a$  so that:

$$\text{Max } \sum_a I$$

Subject to

$$\text{Prob} (I \leq r; a) \leq \alpha$$

It would appear that such a rule of behavior requires that the entrepreneur knows the probability distribution of  $I$  for any action  $a$  that he might choose.

Fortunately we may appeal to the Tchebycheff inequality which permits one to set an upper bound to the  $\text{Prob} (I \leq r; a)$  even when one does not know the probability distribution of  $I$ . The Tchebycheff inequality permits one to assert that:

$$\text{Prob} (|I - \bar{I}| \geq K) \leq \frac{\sigma^2}{K^2}$$

where  $K > 0$ ,  $\sigma^2$  = variance of  $I$  and  $\bar{I}$  = mean of  $I$

It is not hard to show that

$$\text{Prob } (I \leq r) \leq \frac{\sigma^2}{(\bar{I} - r)^2}$$

This means that when  $\frac{\sigma^2}{(\bar{I} - r)^2} \leq \alpha$  then  $\text{Prob } (I \leq r) < \alpha$   
Accordingly,

$$\frac{\sigma^2}{(\bar{I} - r)^2} \leq \alpha$$

becomes the risk restriction which is used.

It is assumed that the entrepreneur knows  $\sigma^2$  and  $\bar{I}$  for each  $a$ , but that he knows nothing more about the probability distribution of  $I$  for each  $a$ .

This formulation of the safety - first principle differs from that of A. D. Roy. He assumes that entrepreneurs minimize the probability of disaster. If they did, then their expected net income for that action which minimized the probability of disaster could be less than zero, i.e. they could be expected to lose money on their portfolio. This implies that there is no asset which the entrepreneur can hold without risk, that is, without the chance of gain or loss.

Sengupta (110) attempts to generalize the decision rules under chance-constrained programming from the viewpoint of safety first principles based on Tchebycheff-type probabilistic inequalities. The latter inequalities are utilized to define

distribution free tolerance levels. The optimization criterion of chance-constrained programming based on the mean and variance is extended to a more generalized formulation based on the Kolmogorov-Smirnov's statistic on the maximum discrepancy of the population and sampling distributions.

Application of chance constrained programming can be found in (30, 29, 83, 89, 64, 1, 32, 31, 28).

#### 2.4. Reliability Programming<sup>1</sup>

Sengupta (113) has extended the chance constrained programming method, interpreting each chance-constraint as a reliability measure. In this approach a tolerance level (in terms of a probability measure), one for each probability constraint is preassigned by the decision-maker and this set of tolerance measures is supposed to indicate the limit up to which constraint violations are permitted. This view of probabilistic linear constraints allows the interpretation of a linear programming model as a system, where each probabilistic constraint can be interpreted as a system component, where each component may have different degrees of reliability (e.g., different tolerance measures). The system reliability would then be dependent on the reliability of its individual components, their interdependence and the choice of the decision variables. Sengupta's objective is to charac-

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<sup>1</sup>This section is based on Sengupta (113, 112, 115).

terize in a simplified framework the method of attaining and optimizing the reliability of a linear programming system under alternative probabilistic variations of constraint parameters.

Sengupta's system reliability approach has two basic differences from the chance-constrained approach. First the system reliability is not preassigned but has to be solved for in an optimal fashion. Second, the statistical theory of system reliability (73, 142), which is essentially based on non-negative life distribution is developed (113) in the production and resource allocation framework of economy theory.

He first considered a linear programming system where each linear constraint is probabilistic only in its resource availabilities. The L.P. system is

$$\max_a z = c'x$$

where

$$x \in X \equiv \{x | Ax \leq b, x \geq 0\} \quad [2.4.1]$$

The resource vector  $b = (b_i)$  is assumed random with probabilistics for its components satisfying the following assumptions:

Assumption 1: The probability distribution of each  $b_i$  is continuous with a non-negative range and mutually independent such that the cumulative distribution

$$F(a_i'x) = \text{Prob}(b_i \leq a_i'x) = 1 - \mu_i; \quad 0 \leq \mu_i \leq 1 \quad [2.4.2]$$

where  $a_i'$  denotes the  $i$ th row of matrix  $A$  in [2.4.1], is assumed known or estimable.

Assumption 2: The non-negative range of the distribution of each  $b_i$  is taken to be  $[0, \infty]$  such that  $R_i(0)=1$ ,  $R_i(\infty)=0$  where

$$R_i(t) = 1 - F(t) = \text{Prob}(b_i > t) = \mu_i; \quad t = a_i'x \quad [2.4.3]$$

It is also assumed that the derivate of  $R_i(t)$  exists for each  $i$  such that  $r_i(t)dt$  where

$$r_i(t) = \frac{d R_i(t)}{dt} \quad [2.4.4]$$

can be interpreted as the probability that the  $i$ th component (i.e. constraint) will fail (i.e. will be violated) at some time in the interval  $(t, t+dt)$ . Note that  $R_i(t)$  is a monotone non-increasing function in the interval  $[0, \infty]$  and it can be interpreted as a measure of reliability.

By assumption one and two the system reliability  $R$  for the linear programming problem [2.4.1] with  $b$  random can be written in one possible formulation as

$$R_0 = \prod_{i=1}^m R_i(t) = \prod_{i=1}^m \mu_i; \quad 0 \leq \mu_i \leq 1 \quad [2.4.5]$$

Sengupta pointed out that this is one of several possible forms of specification of the system reliability for a linear

programming system which is based on three main assumptions.

- (i) The linear programming system consisting of one chance constraints is assumed reliable, if and only if each  $i$ th constraint is feasible and reliable up to the tolerance level  $\mu_i$  ( $i=1, \dots, m$ )
- (ii) The system reliability  $R_0$  in (2.4.5) is bounded in the interval  $[0,1]$ , as also the components reliabilities  $R_i$  or  $\mu_i$ ; hence

$$1 \geq \max_i R_i \geq R_0$$

$$0 \leq \min_m R_i \geq R_0$$

$$\text{when } R_0 = \prod_{i=1}^m \mu_i$$

This implies that the system reliability cannot have a value higher than that of its most reliable component, in other words any component having zero reliability automatically makes the system reliability take on a zero value.

- (iii) The system reliability measure  $R$  is based on the probability of simultaneous non-violation of all  $m$  chance-constraints, each with its reliability level  $\mu_i$  ( $i=1, \dots, m$ ). A measure  $R^0$  based on the probability of simultaneous violation of all  $m$  chance-constraints would be



$$R^0 = 1 - \prod_{i=1}^m (1-R_i(t)) = 1 - \prod_{i=1}^m (1-\mu_i)$$

If we restricted for the present to a measure  $R$  of system reliability defined in [2.4.5] and [2.4.3], and the associated monotonic pay-off function for achieving the level  $R$  of system reliability and then we may hypothesize as in the portfolio analysis model (79, 80) and others (45) a utility function  $u=u(R,z)$  of the decision maker with reliability ( $R$ ) and profits ( $z=c'x$ ) as two arguments satisfying the usual conditions

$$\frac{\partial u}{\partial z} > 0, \quad \frac{\partial u}{\partial R} > 0 \quad \frac{dR}{dz} < 0$$

which imply risk aversion and guarantee in cases the  $u$  function is concave in its arguments the attainment of its maximum value.

A transformed programming problem which incorporates this system reliability may be presented as follows

$$\text{Max } u = w_1 c'x + w_2 \sum_{i=1}^m \ln \mu_i \quad [2.4.6]$$

subject to

$$R_i(a_i'x) \geq \mu_i \quad [2.4.7]$$

$$0 \leq \mu_i \leq 1$$

$$x \geq 0$$

for  $i=1, \dots, m$

For instance if each  $b_i$  followed a two-parameter exponential density

$$p(b_i) = \lambda_i e^{-\lambda(b_i - \theta_i)}; \quad b_i \geq \theta_i \geq 0$$

with parameters  $\lambda_i > 0$  and  $\theta_i > 0$ , then the reliability constraint (2.4.7) becomes

$$e^{-\lambda(a_i'x - \theta_i)} \geq \mu_i$$

taking logarithms we have

$$-\lambda(a_i'x - \theta_i) \geq \ln \mu_i$$

or

$$a_i'x \leq \theta_i - \frac{1}{\lambda_i} \ln \mu_i$$

On defining  $x_{n+i} = -\ln \mu_i$ , the transformed programming problem will be

$$\text{Max } u = w_1 \sum_{j=1}^n c_j x_j - w_2 \sum_{i=1}^m x_{n+i}$$

subject to

$$\sum_{j=1}^n a_{ij} x_j - \frac{1}{\lambda_i} x_{n+i} \leq \theta_i; \quad i=1, 2, \dots, m.$$

$$x_j \geq 0 \quad j=1, \dots, n+m$$

it is possible to add lower bounds to  $x_{n+i}$  variables or any other class of restriction to them.

It is possible to consider several possible distribution forms satisfying the above assumptions. Using distributions other than exponential will produce nonlinear programming problems.

## 3. OPTIMIZATION TECHNIQUES

Nonlinearities frequently arise when a programming model's coefficients are viewed as random variables. For instance we consider any linear programming model in which the  $b_i$  coefficients in the linear inequality constraints are random. To illustrate, suppose the model has two constraints and that the coefficients  $b_i$  are independently distributed, where  $G_i(b)$  represents the probability that the random variable  $b_i$  is at least as large as  $b$ . Suppose we want to select the  $x_j$  so that the joint probability of every constraint being satisfied is at least  $\beta$ :

$$\text{Prob}\left[\sum_{j=1}^n a_{1j}x_j \leq b_1\right] \cdot \text{Prob}\left[\sum_{j=1}^n a_{2j}x_j \leq b_2\right] \geq \beta \quad (0 < \beta \leq 1)$$

The programming constraints equivalent to the above one can be written as

$$\sum_{j=1}^n a_{ij}x_j - y_i = 0 \quad \text{for } i=1,2$$

$$G_1(y) \cdot G_2(y) \geq \beta$$

where the last product leads to a nonlinear restriction on  $y_1$  and  $y_2$ .

The nonlinear programming problem is to determine a vector  $x^0$  that solves the problem

Minimize  $f(x)$

[3.0.1]

subject to

$$g_i(x) \geq 0 \quad i=1,2,\dots,m$$

$$j=1,2,\dots,p$$

where any of the functions  $f(x)$  and  $\{g_i\}$  may be nonlinear.

In this chapter we will only indicate three techniques used in this thesis and they are sequential unconstrained minimization techniques, geometric programming and generalized polynomial programming.

### 3.1. Sequential Unconstrained Minimization Techniques

Anthony V. Fiacco and Garth P. McCormick (49) proposed to transform a mathematical programming problem [3.0.1] into a sequence of unconstrained minimization problems based on an idea proposed by C. W. Carroll (21) as follows:

Define the function

$$P(x,r) = f(x) + r_1 \sum_{i=1}^m \frac{1}{g_i(x)} \quad [3.1.1]$$

where  $r_1$  is a positive constant.

Consider the following condition imposed on the programming problem.

C1:  $R^0 = \{x | g_i(x) > 0, \quad i=1,2,\dots,m \text{ is nonempty}$

C2: The functions  $f_1, g_1, \dots, g_m$  are twice continuously differentiable

C3: For every finite  $k$ ,  $\{x | f(x) \leq k; x \in R\}$  is bounded set,  
 where  $R = \{x | g_i(x) \geq 0, i=1, \dots, m\}$ .

NOTE: Conditions C2-C3 imply the existence of a finite  
 number  $v_0$  where

$$v_0 = \inf_{x \in R} f(x) = \min_{x \in R} f(x)$$

C4: The function  $f$  is convex

C5: The functions  $g_1, \dots, g_m$  are concave

C6: The function  $P(x, r) = f(x) + r \sum_i \frac{1}{g_i(x)}$  is, for each  
 $r > 0$ , strictly convex for  $x \in R^0$

Conditions C4 and C5 imply the convexity of  $P$  in  $R^0$ .

The strict convexity is satisfied if:

- (1)  $f$  is strictly convex; or
- (2) any  $g_i$  is strictly concave; or
- (3) there exist  $n$  independent linear constraints to  
 the problem; or
- (4) the requirement (a special case of (3)) that  $x_i \geq 0$   
 for  $i=1, \dots, n$  are included in the problem.

For every convex programming problem there is an  
 associated problem called its dual.

Primal problem

Min  $f(x)$

[3.1.2]

subject to

$$g_i(x) \geq 0, \quad i=1, \dots, m.$$

The formulation of the dual is due to Wolfe (280, 281)

$$\text{Max } G(x, u) = f(x) - \sum_i u_i g_i(x) \quad [3.1.3]$$

subject to

$$\nabla_x G(x, u) = \vec{0}, \quad [3.1.4]$$

$$u_i \geq 0 \quad i=1, \dots, m$$

If the primal problem has a solution at a point  $\bar{x}$ , then there exists  $\bar{u}$  such that  $(\bar{x}, \bar{u})$  is a solution to the dual, and the extreme values of the problems are equal. In order to prove this it must impose requirements C4 and C5 on the programming problem in addition to differentiability and the Constraint Qualification of Kuhn and Tucker (72).

Theorem 1: (Fiacco-McCormick)

If

- (1)  $R^0$  is non-empty
- (2)  $f(x)$  and  $-g_i(x)$ ,  $i=1, \dots, m$  are convex and twice continuously differentiable
- (3) for every finite  $k$   $\{x | f(x) \leq k; x \in R\}$  is a bounded set
- (4) for every  $r > 0$ ,  $P(x, r)$  is strictly convex, then
  - (a) each function  $P(x, r_k)$  for  $r_k > 0$  is minimized over  $R^0$  at a unique  $x(r_k) \in R^0$  where

$$\nabla_x P[x(r_k), r_k] = \vec{0} \quad [3.1.5]$$

$$(b) \quad \lim_{k \rightarrow \infty} f[x(r_k)] = v_0$$

where

$$v_0 = \inf_{x \in R} f(x) = \min_{x \in R} f(x)$$

As a consequence of equation [3.1.5] the method yields a dual-feasible point at each P minimum, where  $u_i(r_k) = r_k |g_i^2[x(r_k)]|$ ;  $i=1, \dots, m$ .

Theorem 2: (Fiacco-McCormick)

Under the conditions of Theorem 1 the method yields dual feasible points  $[x(r_k), u(r_k)]$  and  $\lim_{k \rightarrow \infty} G[x(r_k), u(r_k)] = v_0$

Since  $v_0$  is the maximum value of  $G(x, u)$  for dual feasible points, the following inequalities obtain

$$G[x(r_k), u(r_k)] \leq v_0 \leq f[x(r_k)]$$

These bounds are of considerable practical importance in deciding when to terminate convergence.

Fiacco and McCormick have further developed this approach which is sometime referred to by the acronym SUMT. For more information the reader can see (48, 51, 47, 81, 141, 78).



### 3.2. Geometric Programming

Geometric programming is a new mathematical programming technique which provides a systematic method for formulating a class of nonlinear optimization problem. The class of functions which geometric programming deals with are positive polynomials or posynomials for short.

Geometric programming is a technique which finds the optimum value without knowing the corresponding policy variables: instead of seeking the optimal values of the independent variables first, it finds the optimal way to distribute the total cost among the various terms of the objective function. Once the optimal allocations are defined, often by inspection of simple linear equations, the optimal cost can be found by routine calculation.

Richard Duffin, Elmor Peterson and Clarence Zener (39) are the authors of geometric programming, one of the most refreshing developments in optimization theory since the invention of the calculus. Geometric programming derives its name from its intimate connection with geometrical concepts, the most important being orthogonality of vectors.

To treat the problem of minimizing a posynomial, we employ the inequality which states that the arithmetic mean is at least as great as the geometric mean. We have that

$$(x_1 - x_2)^2 \geq 0$$

$$x_1^2 - 2x_1x_2 + x_2^2 \geq 0$$

adding  $4x_1x_2$  to both sides

$$x_1^2 + 2x_1x_2 + x_2^2 \geq 4x_1x_2$$

$$(x_1 + x_2)^2 \geq 4x_1x_2$$

taking square root

$$x_1 + x_2 \geq 2\sqrt{x_1x_2}$$

$$\frac{x_1 + x_2}{2} \geq \sqrt{x_1x_2}$$

The Geometric Programming problem is stated as (38):

Primal program:

Find a minimum value of a primal function  $g_0(t)$  subject to the natural constraints

$$t_1 > 0, t_2 > 0, \dots, t_m > 0$$

and forced constraints

$$g_1(t) \leq 1, g_2(t) \leq 1, \dots, g_p(t) \leq 1.$$

where

$$g_k = \sum_{i \in J[k]} c_i t_1^{a_{i1}} t_2^{a_{i2}} \dots t_m^{a_{im}} \quad k=0,1,\dots,p$$

and

$$J[k] = \{m_k, m_{k+1}, m_{k+2}, \dots, n_k\} \quad k=0, 1, \dots, p$$

where

$$m_0=1, \quad m_1=n_0+1, \quad m_2=n_1+1, \dots, m_p=n_{p-1}+1, \quad n_p=n$$

The exponents  $a_{ij}$  are arbitrary real numbers, but the coefficients  $c_i$  are assumed to be positive. Thus the function  $g_k(t)$  are posynomials.

The dual program corresponding to the primal program is stated as:

Dual program:

Find the maximum value of a product function

$$v(\underline{\delta}) = \left[ \prod_{i=1}^n \left( \frac{c_i}{\delta_i} \right)^{\delta_i} \right] \prod_{k=1}^p \lambda_k(\underline{\delta})^{\lambda_k(\underline{\delta})}$$

where

$$\lambda_k(\underline{\delta}) = \sum_{i \in J[k]} \delta_i \quad k=1, 2, \dots, p$$

and

$$J[k] = \{m_k, m_{k+1}, m_{k+2}, \dots, n_k\}, \quad k=0, 1, 2, \dots, p$$

where

$$m_0=1, \quad m_1=n_0+1, \quad m_2=n_1+1, \dots, m_p=n_{p-1}+1, \quad n_p=n$$

The factor  $c_i$  are assumed to be positive and the vector variable  $\delta = (\delta_1, \dots, \delta_n)$  is subject to linear constraints:

positive condition

$$\delta_1 \geq 0, \delta_2 \geq 0, \dots, \delta_n \geq 0$$

normality condition

$$\sum_{i \in J[0]} \delta_i = 1$$

and orthogonality condition

$$\sum_{i=j}^n a_{ij} \delta_i = 0 \quad j=1,2,\dots,m$$

the coefficients  $a_{ij}$  are real numbers.

The difference between the number of variables and the number of independent linear equations is conventionally called the number of degrees of freedom, as we have seen there are  $n$  orthogonality conditions, one for each variable  $t_i$ , a single normality condition and  $m$  weights, one for each term. Hence the equations have  $m-(n+1)$  degrees of freedom. Duffin and Zener (39) suggest calling this quantity the degree of difficulty.

Wilde (138) says that geometric programming is a challenging situation for any reader who has gotten this far into the subject, for most systems can be decomposed into components, each with its own cost or revenue. Component behavior in most engineering systems can usually be expressed as products of powers of the design variables, as it is testified by the frequency of logarithmic graphs in the

technical literature. The effect of scale of operation is often expressed by such approximations as the six-tenths rules (19), which states that the cost of a piece of equipment varies as the  $\frac{6}{10}$  power of its capacity. For problems with few degrees of difficulty, geometric programming promises to yield fast, accurate solutions to horribly non-linear problems. The reader should refer to (38, 37, 19, 143, 144, 5) for further information.

### 3.3. Generalized Polynomial Programming

The positive coefficients of the posynomials are needed because they are raised to fractional powers in the geometric inequality, an operation forbidden to negative numbers. Passy and Wilde (98) developed the quasiduality theory of generalized polynomial programming. Geometric programming is now applicable to any problem involving generalized polynomials (negative coefficients permitted) in the objective function. Generalized polynomial inequalities of either sense can also be handled.

Passy and Wilde considered  $M+1$  real generalized polynomial functions  $g_m(x)$  of  $N$  real positive primal variables  $x_n$ :

$$g_m(x) \equiv \sum_{t=1}^{T_m} \sigma_{mt} c_{mt} \prod_{n=1}^N x_n^{a_{mnt}} \quad m=0,1,\dots,M$$

where

$$\sigma_{mt} = \pm 1$$

$$c_{mt} > 0$$

$$x_m > 0$$

and the  $a_{mtn}$  are any real numbers. Assume the signum function  $\sigma_{mt}$ , the coefficients  $c_{mt}$ ,  $t_m$  (the number of terms in  $g_m$ ), and the  $a_{mtn}$  are all given. Then the optimization problem will be

$$\min_{x>0} g_0(x) \equiv g_0(x^0) \equiv g_0^0$$

subject to

$$0 < \sigma_m g_m^{\sigma_m} \leq 1 \quad m=1, \dots, M.$$

Where the  $\sigma_m$  are known signum functions. The functions  $g_m$  are assumed to satisfy the Kuhn-Tucker constraint qualification (72). Finding  $x^0$  is in general a nonconvex programming problem for which no good general solution method exists.

They show that in nontrivial circumstance this problem can be solved by working with a set of real finite auxiliary variables  $\delta_{mt}$ , one for each term of the  $g_m$ , which must all be finite and nonnegative for  $m=0, 1, \dots, M$

$$0 \leq \delta_{mt} < \infty;$$

and must satisfy the linear normality condition:

$$\delta_{00} \equiv \sigma_0 \sum_{t=1}^{T_0} \sigma_{0t} \delta_{0t} = 1; \quad [3.3.1]$$

and the  $N$  linear orthogonality conditions:

$$\sum_{m=0}^M \sum_{t=1}^{T_m} \sigma_{mt} a_{mnt} \delta_{mt} = 0 \quad n=1, \dots, N; \quad [3.3.2]$$

and the  $M$  linear inequality constraints

$$\delta_{m0} \equiv \sigma_m \sum_{t=1}^{T_m} \sigma_{mt} \delta_{mt} \geq 0 \quad m=1, \dots, M;$$

with the qualification that

$$\delta_{mt} = 0$$

if and only if

$$\delta_{m0} = 0$$

where  $\sigma_0$  is not specified in advance and must be chosen to satisfy the constraints.

From these auxiliary variables is formed the product function

$$v(\underline{\delta}, \sigma_0) \equiv \sigma_0 \left[ \prod_{m=0}^M \prod_{t=1}^{T_m} \left( \frac{c_{mt} \delta_{mt}}{\delta_{mt}} \right)^{\sigma_0} \right]$$

where  $\underline{\delta}$  gathered the finite auxiliary variables  $\delta_{mt}$ .

They show that if  $g_0(x)$  has a minimum at a finite point in  $T$ , the domain of definition of  $\underline{x}$  then there exists auxiliary variables  $\delta^0, \sigma^0$  such that

$$v(\delta^0, \sigma_0^0) = g_0^0$$

and the optimal  $x^0$  can be found by solving any  $N$  independent equations chosen from among the following equations, linear in the variables  $\log x_n$ :

$$\sum_{n=1}^N a_{0tn} (\log x_n) = \log \left( \frac{\sigma_0^0 \delta_{0t} g_0^0}{c_{0t}} \right) \quad t=1, \dots, T_0$$

$$\sum a_{mnt} (\log x_n) = \log \left( \frac{\delta_{mt}}{\delta_{m0} c_{0t}} \right) \quad t=1, \dots, T_m$$

$$m=1, \dots, M, \delta_{m0} \neq 0$$

From these logarithms the  $x^0$  are readily found, when

$$\sum_{m=0}^N T_m = N+1$$

The system of linear equations [3.3.1], [3.3.2] has a unique solution (degree of difficulty equal to zero). As the number of degree of difficulty

$$D = \sum_{m=0}^M T_m - N - 1$$

increases, nonlinear computations and some trial and error methods are needed to find  $\delta^0$  and  $\sigma_0^0$ .

A computer program of generalized polynomial programming is available in Blau (16). For further information the reader can see (97, 16, 98).



#### 4. ECONOMIC APPLICATIONS

##### 4.1. Production Planning

Production planning (58) is concerned with specifying how the production resources of the firm are to be employed over some future time period in response to the predicted or forecasted demand for the product or services. The objective of production planning is to minimize the total cost of meeting demand within the constraints of a given system design. It could, of course consider the question of re-designing the system or adding physical capacity as part of the planning problem but these issues are here arbitrarily eliminated from consideration.

C. C. Holt, F. Modigliani J. F. Muth and H. A. Simon (68, 67) at the Carnegie Institute of Technology in 1955, conducted perhaps the most comprehensive experiment in production planning. The problem was to determine a linear decision rule for making production and labor-force decisions in successive time periods. The planning variables are capacity factors which can be manipulated by management and for which capital investment is not important, that would minimize the expected value of total cost over a large number of periods.

The balancing labor cost of changing labor force and inventory connected cost are assumed to be quadratic functions

of the production quantities  $P_t$  and work force levels  $W_t$ .

The following notation is used

$W_t$  = the number of workers required for the period  
 $t$ ;  $t=1,2,\dots,T$

$P_t$  = the number of units to be produced for the  
 period  $t$

$I_t$  = the inventory minus backlogs at the end of period  $t$

$S_t$  = forecast of the number of units to be ordered for  
 shipment during the period  $t$

$c_k$  = cost coefficients to be determined for a given  
 plant or situation (constants)

Specifically, the cost elements for period  $t$  are

Regular payroll	$[c_1 W_t$
Hiring and layoff	$+ c_2 (W_t - W_{t-1})^2$
Overtime	$+ c_3 (P_t - c_4 W_t)^2 + c_5 P_t - c_6 W_t$
Inventory and shortage	$+ c_7 (I_t - c_8 - c_9 S_t)^2]$

when  $t=1,2,\dots,T$  and the inventory level  $I_t$  obeys the

$$\text{rule } I_t = I_{t-1} + P_t - S_t$$

After the total cost function is obtained, the decision rule that minimizes the expected value of the total cost function is obtained by differentiating with respect to each decision variable. This result is a set of linear equations whose solution, in turn yields the decision rule. It is

noted that the assumption of quadratic cost function results in linear equations after differentiating, and finally in linear decision rules. The obvious advantage is that differential calculus may be employed to arrive at a system of linear equations for optimal quantities  $P_t$  and  $W_t$ .

The resulting decision rules are of the following form.

$$P_t = \sum_{t=1}^T a_t S_t + bW_{t-1} + c I_{t-1} + d$$

$$W_t = \sum_{t=1}^T l_t S_t + f_t W_{t-1} + g_t I_{t-1} + h$$

Where all coefficients only depend on the cost parameters and may therefore be determined once for all as long as the cost parameters do not change.

An implicit assumption of decision analysis is that the underlying cost structure remains constant over many periods. It is not always realistic to make an estimate of the cost structure once and for all, the quadratic cost estimate will, from time to time, require revision in order to be reasonably accurate (67, p. 90). Other assumptions are perfect competition, homogeneous work and one product firm.

The cost coefficients used below will be the same as used by Holt, Modigliani, Muth and Simon in the paint factory (67, p. 73) and they are

$$c_1 = 340$$

$$c_{13} = 0$$

$$c_2 = 64.3$$

$$c_{11} = 0.$$

$$c_3 = 0.20$$

$$c_4 = 5.67$$

$$c_5 = 51.2$$

$$c_6 = 281.$$

$$c_{12} = 0.$$

$$c_7 = 0.0825$$

$$c_8 = 320.$$

$$c_9 = 0.$$

#### 4.1.1. A reliability model

A system reliability approach to the following production programming model is developed here for the case of chance-constrained restrictions.

The problem is:

$$\begin{aligned} \text{Min } \sum_{t=1}^T & [(c_1 - c_6)W_t + c_2(W_t - W_{t-1})^2 + c_3(P_t - c_4W_t)^2 \\ & + c_5P_t + c_7(I_t - c_8 - c_9\bar{S}_t)^2] \end{aligned}$$

subject to

$$\text{Prob}(P_t + I_{t-1} \geq S_t) \geq u_t \quad t=1, \dots, T$$

$$0 \leq u_t \leq 1$$

where the variable sales  $S$  is a random variable assumed to be a two-parameter exponential density function

$$f(S) \equiv f(S, \mu, \theta) = \mu e^{-\mu(S-S_0)} \quad \begin{matrix} S_0 \leq S < \infty \\ \theta = S_0 \end{matrix}$$

where

$$\theta = \text{minimum sale} = S_0$$

and  $\mu$  is evaluated as:

$$E(S) = \int_{S_0}^{\infty} S \mu e^{-\mu(S-S_0)} dS = \mu e^{\mu S_0} \int_{S_0}^{\infty} S e^{-\mu S} dS$$

integrating by parts we have

$$\begin{aligned} E(S) &= \mu e^{\mu S_0} \left[ -\frac{S}{\mu} e^{-\mu S} \Big|_{S_0}^{\infty} - \int_{S_0}^{\infty} -\frac{1}{\mu} e^{-\mu S} dS \right] \\ &= \mu e^{\mu S_0} \left[ -\frac{S}{\mu} e^{-\mu S} \Big|_{S_0}^{\infty} - \frac{1}{\mu^2} e^{-\mu S} \Big|_{S_0}^{\infty} \right] \\ &= \mu e^{\mu S_0} \left[ \frac{S_0}{\mu} e^{-\mu S_0} + \frac{1}{\mu^2} e^{-\mu S_0} \right] \end{aligned}$$

$$E(S) = S_0 + \frac{1}{\mu}$$

$$\frac{1}{\mu} = E(S) - S_0$$

but if  $E(S) = \bar{S}_t$

$$\mu = \frac{1}{\bar{S}_t - S_0}$$

but if we had

$$F(q) = \text{Prob } (S \leq q)$$

we know that

$$F(q) = \mu \int_{S_0}^q e^{-\mu(S-S_0)} dS = \mu e^{\mu S_0} \int_{S_0}^q e^{-\mu S} dS$$

$$F(q) = \mu \frac{e^{+\mu S_0}}{(-\mu)} (e^{-\mu q} - e^{-\mu S_0})$$

$$F(q) = 1 - e^{+\mu(S_0 - q)}$$

the reliability measure  $R(q)$  is defined as

$$R(q) = 1 - F(q)$$

then

$$R(q) = e^{+\mu(S_0 - q)} = e^{-\mu(q - S_0)}$$

Therefore for the  $t^{\text{th}}$  constraint we have:

$$\text{Prob } (S_t \leq P_t + I_{t-1}) \geq u_t$$

then

$$1 - R(P_t + I_{t-1}) \geq u_t$$

$$1 - e^{-\mu(P_t + I_{t-1} - S_0)} \geq u_t$$

$$1 - u_t \geq e^{-\mu(P_t + I_{t-1} - S_0)}$$

taking logarithms to both side of the last expression we have:

$$\ln(1-u_t) \geq -\mu(P_t + I_{t-1} - S_0)$$

dividing by  $-\mu$  we have:

$$-\frac{1}{\mu} \ln(1-u_t) \leq P_t + I_{t-1} - S_0$$

rearrange the terms to get

$$P_t + I_{t-1} + \frac{1}{\mu} \ln(1-u_t) \geq S_0$$

If we make

$$y_t \equiv -\ln(1-u_t)$$

and

$$\lambda \equiv \frac{1}{\mu}$$

that is

$$\lambda = \bar{S}_t - S_0$$

then,

$$P_t + I_{t-1} - \lambda y_t \geq S_0$$

The use of exponential distribution is motivated by its wide applications in statistical theory of reliability (142, 73) and the fact that it retains the constraint linearity of the transformed model, after the reliability measures are incorporated. The exponential distribution provides a limiting distribution in the class of distributions with nonnegative domains, under certain conditions (9), as the

normal distribution under certain conditions provides a limiting distribution under the central limit theorem for a wide class of random variables. If we assume that the random variable  $S_t$ 's are statistically independent and it is assumed that the system reliability  $R$  for a mathematical programming model as a whole must be an index combining the component reliabilities  $R_t$ , then one possible measure of system reliability is: (113, 112, 115)

$$R \equiv 1 - \prod_{t=1}^T R_t \equiv 1 - \prod_{t=1}^T (1 - u_t) \quad [4.1.1]$$

This measure  $R$  of system reliability is based on two main assumptions (115):

- (i) The quadratic programming system consisting of  $t$  chance constraints is assumed if and only if each  $t^{\text{th}}$  constraint is feasible and reliable up to the tolerance level  $u_t$  ( $t=1, \dots, T$ )
- (ii) The system reliability measure  $R$  in [4.1.1] is bounded in the interval  $[0,1]$  as also the reliability component  $R_t$ . This concept of  $R$  in [4.1.1] will be used in our application subject to specified lower and upper bound restrictions on each  $u_t$ . This view of  $R$  preserves the quadratic structure of our program.



Note that [4.1.1] is one of several possible forms of specification of the system reliability for quadratic programming problems.

We may now present a way of incorporating the system reliability  $R$  in [4.1.1] into our original quadratic programming problem of probabilistic linear constraints. It is possible to associate a monotonic pay-off function with  $R$  and hence a utility function  $U=U(R,-z)$  of the problem maker with reliability  $R$  and costs  $(z=p'x+x'cx)$  as two arguments satisfying the usual conditions

$$\frac{\partial u}{\partial (-z)} > 0 \quad \frac{\partial u}{\partial R} > 0 \quad \frac{dR}{d(-z)} < 0 \quad [4.1.2]$$

which imply risk aversion and guarantee the attainment of the maximal value of the  $U$  function in the cases where it is concave in its arguments. One possible choice of the utility function satisfying the conditions [4.1.2] is

$$U = \omega_1 \left\{ \sum_{t=1}^T [c_1 - c_6) w_t + c_2 (w_t - w_{t-1})^2 + c_3 (P_t - c_4 w_t)^2 + c_5 P_t + c_7 (I_t - c_8 - c_9 \bar{S}_t)^2 \right\} - \omega_2 \sum_{t=1}^T -\ln(1 - u_t)$$

where  $\omega_1$  and  $\omega_2$  are scalar nonnegative constant weights assumed known such that  $\omega_1 + \omega_2 = 1$ .

In the present case the transformed programming problem which incorporates the system reliability may be presented as follows:

$$\begin{aligned} \text{Min } \omega_1 \{ \sum_{t=1}^T [(c_1 - c_6)w_t + c_2(w_t - w_{t-1})^2 + c_3(P_t - c_4w_t)^2 \\ + c_5P_t + c_7(I_t - c_8 - c_9\bar{S}_t)^2] - \omega_2 \sum_{t=1}^T y_t \end{aligned}$$

subject to

$$w_t \geq w_0$$

$$P_t + I_{t-1} - \lambda y_t \geq S_0$$

$$y_t \geq y^*$$

$$y_t \leq y_* \quad [t=1, \dots, T]$$

$$y^*, y_* \geq 0$$

where

$w_0$  is a preassigned minimum labor force level

$y^*$  is an upper bound of variable  $y$  (number  $y_t = -\ln(1-u_t)$ )

and it is supposed to be known

$y_*$  is a lower bound of variable  $y$  and also known.

Our problem can be written as

$$\begin{aligned} \text{Min } \omega_1 [ (c_1 - c_6) \sum_{t=1}^{12} w_t + (2c_2 + c_3 c_4^2) \sum_{t=1}^{11} w_t + (c_2 + c_3 c_4^2) w_{12}^2 \\ - 2c_2 \sum_{t=1}^{11} w_t w_{t+1} - 2w_0 c_2 w_1 \end{aligned}$$

$$\begin{aligned}
& -2c_3c_4 \sum_{t=1}^{12} P_t w_t + c_5 \sum_{t=1}^{12} P_t + c_3 \sum_{t=1}^{12} P_t^2 + c_7 \sum_{t=1}^{12} I_t^2 \\
& -2c_7(c_8+c_9\bar{S}_t) \sum_{t=1}^{12} I_t \\
& (+ 24c_7c_8c_9\bar{S}_t + 12c_7c_8^2 + c_7^2w_0^2) ] - w_2 \sum_{t=1}^{12} y_i
\end{aligned}$$

subject to

$$w_t \geq w_0$$

$$P_t + I_{t-1} - \lambda y_t \geq S_0$$

$$y_t \geq y^*$$

$$y_t \leq y_* \quad \text{for } t=1, \dots, 12$$

$$y^*, y_* \geq 0$$

This problem is a quadratic programming problem of the following form

$$\text{Min } p'x - \frac{1}{2}x'cx$$

subject to

$$Ax \leq b$$

that is a quadratic objective function subject to linear constraints, where

$$c = \begin{bmatrix} \underline{w}_1 & \underline{p}_{12} & 0 & 0 \\ \underline{p}_{12} & \underline{p}_1 & 0 & 0 \\ 0 & 0 & \underline{I}_1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}; \quad x = \begin{bmatrix} \underline{w} \\ \underline{p} \\ \underline{I} \\ \underline{y} \end{bmatrix}$$

$$p = \begin{bmatrix} w_p \\ p_p \\ I_p \\ y_p \end{bmatrix} ; \quad b = \begin{bmatrix} w_b \\ I_b \\ y_b^* \\ y_{*b} \end{bmatrix} \quad \text{and} \quad A = \begin{bmatrix} \underline{w}^1 & 0 & 0 & 0 \\ 0 & \underline{p}^1 & \underline{I}^1 & \underline{y}^1 \\ 0 & 0 & 0 & \underline{y}^2 \\ 0 & 0 & 0 & \underline{y}^3 \end{bmatrix}$$

Let us define our submatrices and reactors as

$$\begin{matrix} \underline{w}_1 \\ (12 \times 12) \end{matrix} = \begin{bmatrix} 4c_2 + 2c_4^2 c_3 & -2c_2 & 0 & 0 \\ -2c_2 & 4c_2 + 2c_4^2 c_3 & -2c_2 & 0 \\ 0 & & 4c_2 + 2c_4^2 c_3 & -2c_2 \\ & & & 4c_2 + 2c_4^2 c_3 & -2c_2 \\ 0 & 0 & & & 2c_2 + 2c_4^2 c_3 \end{bmatrix}$$

$$\begin{matrix} \underline{p}_{12} \\ (12 \times 12) \end{matrix} = \begin{bmatrix} -2c_4 c_3 & 0 & & & \\ 0 & -2c_4 c_3 & 0 & & \\ 0 & 0 & -2c_4 c_3 & & \\ & & & 0 & \\ 0 & & & & -2c_4 c_3 \end{bmatrix} ;$$

$$\underline{p_1}_{(12 \times 12)} = \begin{bmatrix} 2c_3 & 0 & & \\ 0 & 2c_3 & & \\ & & 0 & \\ & & 0 & 2c_3 \end{bmatrix} ;$$

$$\underline{I_1}_{(12 \times 12)} = \begin{bmatrix} 2c_7 & 0 & & \\ 0 & 2c_7 & & \\ & & 0 & \\ & & 0 & 2c_7 \end{bmatrix} ;$$

$$\underline{w}_{(12 \times 1)} = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ \vdots \\ \vdots \\ w_{12} \end{bmatrix} ; \quad \underline{p}_{(12 \times 1)} = \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ \vdots \\ \vdots \\ p_{12} \end{bmatrix} ; \quad \underline{I}_{(12 \times 1)} = \begin{bmatrix} I_1 \\ I_2 \\ I_3 \\ \vdots \\ \vdots \\ I_{12} \end{bmatrix} ; \quad \underline{y}_{(12 \times 1)} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ \vdots \\ y_{12} \end{bmatrix} ;$$

$$\begin{matrix} \underline{w}_p \\ (12 \times 1) \end{matrix} = \begin{bmatrix} c_1 - c_6 - 2c_2 w_0 \\ c_1 - c_6 \\ \vdots \\ c_1 - c_6 \end{bmatrix}; \quad \begin{matrix} \underline{p}_p \\ (12 \times 1) \end{matrix} = \begin{bmatrix} c_5 \\ c_5 \\ \vdots \\ c_5 \end{bmatrix}; \quad \begin{matrix} \underline{I}_p \\ (12 \times 1) \end{matrix} = \begin{bmatrix} -2c_7(c_8 + c_9 \bar{s}_t) \\ \vdots \\ -2c_7(c_8 + c_9 \bar{s}_t) \end{bmatrix};$$

$$\begin{matrix} \underline{y}_p \\ (12 \times 1) \end{matrix} = \begin{bmatrix} -1 \\ -1 \\ -1 \\ \vdots \\ -1 \end{bmatrix};$$

$$\begin{matrix} \underline{w}_p \\ (12 \times 1) \end{matrix} = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}; \quad \begin{matrix} \underline{I}_p \\ (12 \times 1) \end{matrix} = \begin{bmatrix} -I_0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}; \quad \begin{matrix} \underline{y}_b^* \\ (12 \times 1) \end{matrix} = \begin{bmatrix} \ln(1-u_t) \\ \vdots \\ \ln(1-u_t) \end{bmatrix};$$

$$\begin{matrix} \underline{y}_{*b} \\ (12 \times 1) \end{matrix} = \begin{bmatrix} \ln(1-u_t) \\ \vdots \\ \ln(1-u_t) \end{bmatrix};$$

$$\underline{w}^1_{(12 \times 12)} = \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & 1 & \\ & & & 1 \end{bmatrix};$$

$$\underline{p}^1_{(12 \times 12)} = \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & 1 & \\ & & & 1 \end{bmatrix};$$

$$\underline{I}^1_{(12 \times 12)} = \begin{bmatrix} 0 & & & \\ 1 & 0 & & \\ & 1 & 0 & \\ & & & 1 \end{bmatrix}; \quad \underline{y}^1_{(12 \times 12)} = \begin{bmatrix} -\lambda & & & \\ & -\lambda & & \\ & & & \\ & & & -\lambda \end{bmatrix}$$

$$\underline{y}^2 = \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & & \\ & & & 1 \end{bmatrix} \quad \text{and} \quad \underline{y}^3 = \begin{bmatrix} -1 & & & \\ & -1 & & \\ & & & \\ & & & -1 \end{bmatrix}$$

As we know the values of  $u_t$  must be between the interval  $[0,1]$  thus we have preassigned an upper bound of 0.999 to  $y^*$  and a lower bound of 0.5 to  $y_*$ . Then for

$$y_t = -\ln(1-u_t)$$

we have that:

<u>for a lower bound</u>	<u>for an upper bound</u>
$u_t \geq .5$	$u_t \leq .999$
multiplying by -1	multiplying by -1
$-u_t \leq -.5$	$-u_t \geq -.999$
adding 1 to both sides	adding 1 to both sides
$1-u_t \leq .5$	$1-u_t \geq .001$
taking logarithms of both sides	taking logarithms of both sides
$\ln(1-u_t) \leq \ln .5$	$\ln(1-u_t) \geq \ln .001$
$\ln(1-u_t) \leq -.69315$	$\ln(1-u_t) \geq -6.90776$
multiplying both sides by -1	multiplying both sides by -1
$-\ln(1-u_t) \geq .69315$	$-\ln(1-u_t) \leq 6.90776$
then we have	then we have
$y_t \geq .69315$	$y_t \leq 6.90776$

We have developed a programming system for the present IBM system 360 Model 65 of the I.S.U. computer center, using the Zorrilla program (125, 146) to handle the quadratic programming problem which uses the procedure developed



by Van de Panne and Whinston (96, 95). The programming system is so time varying and needs only four cards; for more details see the Appendix A.

We have a problem to determine how large  $\lambda$  can be (i.e. how much it will be possible to vary the interval  $(\bar{S}_t - S_0)$  in order to deal with a significant case; we might have used the theoretical development of Bhattacharya and Holla (15). They have studied the exponential distribution with the probability density function

$$f(x, \theta) = \frac{1}{\theta} e^{-x/\theta} \quad (x > 0, \theta > 0) \quad [4.1.3]$$

as a model for life-lengths of materials which is most thoroughly explored in (42, 43, 41). This distribution has a number of desirable mathematical properties, but its usefulness is sharply limited due to the property of the constancy of failure rate. For life-lengths of materials for which this property is no longer valid, normal distribution sometimes proves to be a nice analytical tool. Further, there exists many life-test situations which can be described as a mixture of two or more distributions (101, 77). Such situations arise because of the heterogeneity of the material involved in the life-test. However, if continuous variations are taking place during the manufacturing process, which is more or less inevitable, the quality of the produced items will be so much heterogeneous that the method of mixtures mentioned

above may not be adequate enough to describe a life-test situation involving these items. In our case we only have to consider such a situation in which the mean life involved in [4.1.3] is subject to continuous stochastic deviations with a maximum permissible limit  $\delta(>0)$  on either side of the mean. Assuming that these deviations are uniformly distributed over the range mentioned above, a new model for life length of materials is obtained.

We must remember that we defined the hazard ratio as

$$z(t) = \frac{f(t)}{1-F(t)}$$

The main reason for defining the  $z(t)$  function is that it is often more convenient to work with than  $f(t)$ , (123, 103). For example, in our case  $f(t)$  is an exponential, the most common failure density one deals with in reliability work. Then

$$f(t) = \frac{1}{\theta} e^{-t/\theta}$$

$$F(t) = 1 - e^{-t/\theta}$$

$$1-F(t) = e^{-t/\theta}$$

$$z(t) = \frac{f(t)}{1-F(t)} = \frac{\frac{1}{\theta} e^{-t/\theta}}{e^{-t/\theta}} = \frac{1}{\theta}$$

Thus, an exponential failure density compounds to constant hazard functions as pointed out above.

Bhattacharya and Holla considered a probability density function  $f(x, \lambda)$  of the same form as [4.1.3], where the parameter  $\lambda$  is itself a random variable, distributed uniformly over a range  $[\theta - \delta, \theta + \delta]$  with  $\theta > \delta > 0$ . Then using the result

$$\int_x^\infty e^{-t} t^{-1} dt = e^{-x} \phi[1; 1; x]$$

where  $\phi[a; b; x]$  is the well-known function due to Tricomi (44, p. 255) defined for any real  $a > 0$ , it is obtained for the over all distribution of  $x$ . The following probability density function:

$$\begin{aligned} f(x) &= \frac{1}{2\delta} \int_{\theta-\delta}^{\theta+\delta} \frac{1}{\lambda} e^{-x/\lambda} d\lambda \\ &= \frac{1}{2\delta} \left\{ \exp(-x/(\theta+\delta)) \phi\left[1; 1; \frac{x}{\theta+\delta}\right] \right. \\ &\quad \left. - \exp(-x/(\theta-\delta)) \phi\left[1; 1; \frac{x}{\theta-\delta}\right] \right\} \\ &\quad (x > 0, \theta > \delta > 0) \end{aligned} \quad [4.1.4]$$

When  $\delta$  approaches zero the uniform distribution considered above degenerates into a single point  $\theta$  with the whole probability mass concentrated at this point and we obtain the usual exponential distribution in the limit. It is easy to see mathematically

$$\lim_{\delta \rightarrow 0} f(x) = \frac{1}{\theta} \exp(-x/\theta) \quad (x > 0, \theta > 0)$$

The moments of the distribution [4.1.4] may be defined as

$$\mu'_r = \frac{r!}{(r+1)!} \left[ \frac{(\theta+\delta)^{r+1} - (\theta-\delta)^{r+1}}{2\delta} \right]$$

In particular the first two moments are

$$\mu'_1 = \theta$$

$$\mu'_2 = \frac{2}{3}(3\theta^2 + \delta^2)$$

The cumulative distribution function corresponding to [4.1.4] is

$$F(y) = \int_0^y f(x) dx = \frac{1}{2\delta} \int_{\theta-\delta}^{\theta+\delta} (1 - e^{-y/\lambda}) d\lambda$$

Then the failure rate is given by

$$z(t) = \frac{f(t)}{1-F(t)} = \frac{\frac{1}{2\delta} \int_{\theta-\delta}^{\theta+\delta} \frac{1}{\lambda} e^{-t/\lambda} d\lambda}{1 - \frac{1}{2\delta} \int_{\theta-\delta}^{\theta+\delta} (1 - e^{-t/\lambda}) d\lambda}$$

$$z(t) = \frac{\int_{\theta-\delta}^{\theta+\delta} \frac{1}{\lambda} e^{-t/\lambda} d\lambda}{\int_{\theta-\delta}^{\theta+\delta} e^{-t/\lambda} d\lambda}$$

unlike we show for the exponential distribution, this failure is not independent of  $t$ .

For estimation of the parameters we have to have a random sample  $(x_1, x_2, \dots, x_n)$  from the distribution [4.1.4] and by the usual procedure of moments we have

$$\hat{\theta} = v_1$$

$$\hat{\delta} = \left( \frac{3}{2} v_2 - 3v_1^2 \right)^{\frac{1}{2}}$$

where

$$v_r = \frac{1}{n} \sum_{i=1}^n x_i^r$$

We have, taking a much simpler approach, in a sense of simulation we have evaluated problems for different  $\lambda$  (i.e.  $\bar{S}_t - S_0$ ) we observe in Table 4.1.1 these values

Table 4.1.1. Parameter values

$\lambda$	$\bar{S}$	$S_0$	Table
50	500	450	4.1.3
200	500	300	4.1.4
250	500	250	4.1.5
300	1100	800	4.1.6

We had observed that we could get better cases for  $\lambda=200$  that is we get a little more variability in the probability. In Table 4.1.3, 4.1.4 and 4.1.5 we can observe how the change in labor force, production and inventory level are adjusting to the probability level to achieve a production

planning which it is desired.

In the present case we faced one other problem: How large will be our production planning horizon (that is, how large could  $T$  be?) This point opens a very interesting question in the class of control theory problems (33, 4). Here we just solve problems with  $T$  up to 12 periods and we use as a criterion the stability of the solutions (i.e. steady-state values of our instrument variables).

We observe in Table 4.1.2 and in Figures 4.1.1, 4.1.2, 4.1.3 and 4.1.4, when  $T=12$ , a steady-state of values in instrument variables is achieved at  $T=6$ . Therefore, we only need to study production planning up to the sixth period in all cases.

As the cost coefficients and actual production, inventory and labor force had been coded to protect the company, we are dealing here with hypothetical cases of sales, in other words the average sale and minimum sales are not very representative about the labor force which always after certain values of  $t$  less than  $T$  goes to the minimum value given as restrictions.

We can also say that initial labor force and minimum labor restriction play a crucial role in our production planning problem, as they are shown in the tables below.

We also point out the influence of initial inventory in the probability level. We can see that the optimal inventory

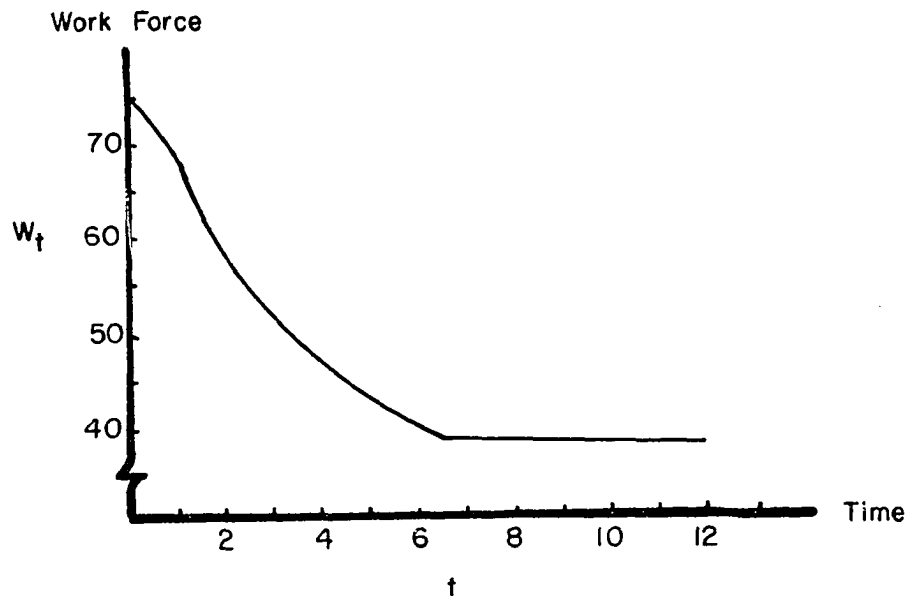


Figure 4.1.1. Work Force

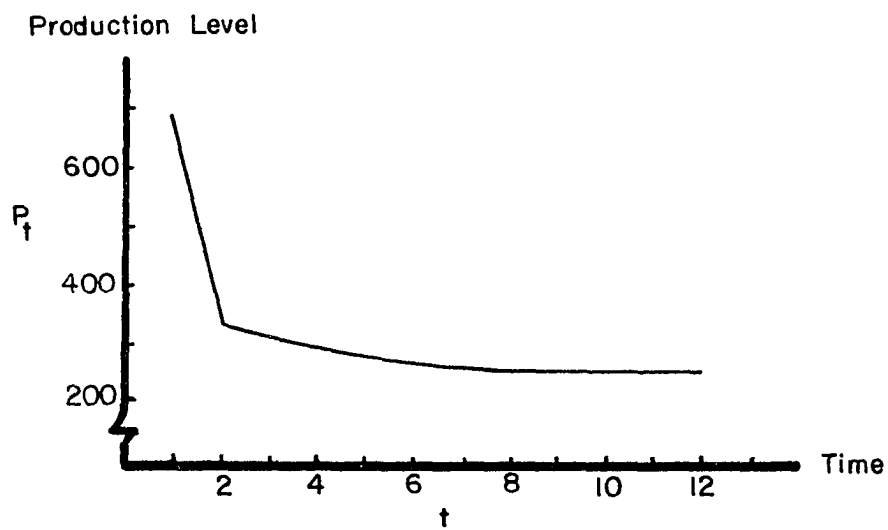


Figure 4.1.2. Production

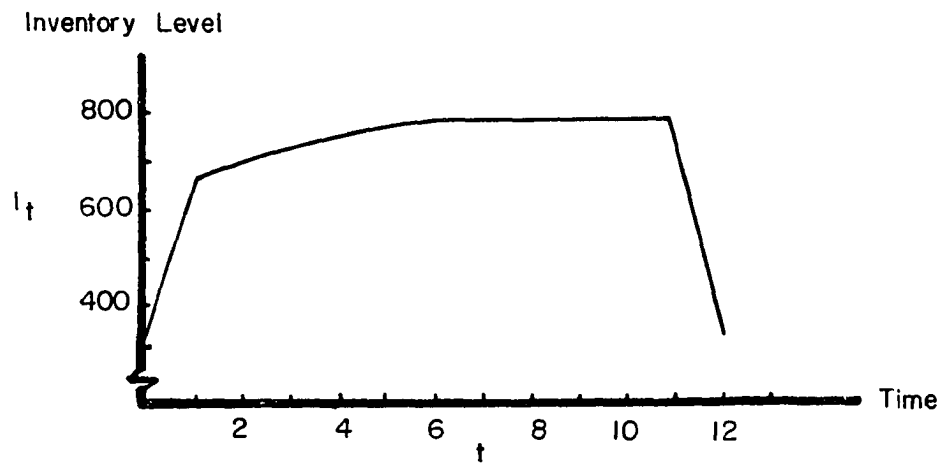


Figure 4.1.3. Inventory

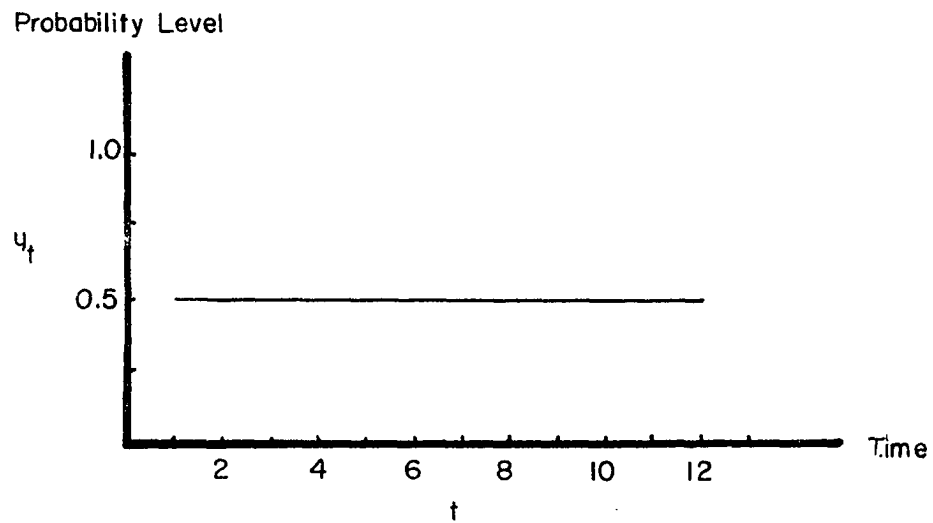


Figure 4.1.4. Probability Level



Table 4.1.2. Optimal solutions of the quadratic program  
(exponential reliability)

<hr/>					
<u>t=12</u>	$\omega_1 = .8$	$w_0 = 75$	$\bar{S} = 1100$	$I_0 = 320$	
	$\omega_2 = .2$	$w_i \geq 40$	$S_0 = 800$	Total cost=882,642.36	
Time	Work Force	Production level	Inventory level	Reliability	Probability level
t	$w_t$	$p_t$	$I_t$	$y_t$	$u_t$
<hr/>					
1	70	687.945	653.306	.69315023	.5
2	61	354.640	683.053	.69315023	.5
3	53	324.892	705.736	.69315023	.5
4	48	302.210	722.016	.69315023	.5
5	44	285.930	732.368	.69315023	.5
6	41	275.578	737.094	.69315023	.5
7	40	270.851	737.094	.69315023	.5
8	40	270.851	737.094	.69315023	.5
9	40	270.851	737.094	.69315023	.5
10	40	270.851	737.094	.69315023	.5
11	40	270.851	737.094	.69315023	.5
12	40	270.851	320.000	.69315023	.5
<hr/>					
$u_i \leq .999; u_i \geq .5$					
<hr/>					

Table 4.1.3. Optimal solutions of the quadratic program  
(exponential reliability)

$\omega_1 = .8 \quad w_0 = 90 \quad S = 500 \quad I_0 = 320$ $\omega_2 = .2 \quad w_i \geq 75 \quad \bar{S}_0 = 450 \quad \text{Total cost} = 158,611.04$					
<u>t=6</u>					
Time	Work	Production	Inventory	Reliability	Probability
t	Force	level	level		level
	$w_t$	$p_t$	$I_t$	$y_t$	$u_t$
1	82	335.378	320.03	4.1075573	.983
2	76	303.843	320.03	3.47745	.969
3	75	297.263	320.03	3.3458491	.904
4	75	297.263	320.03	3.3458491	.904
5	75	297.263	320.03	3.3458491	.904
6	75	297.263	320.03	3.3458491	.904

Table 4.1.4. Optimal solutions of the quadratic program  
(exponential reliability)

$\omega_1 = .8 \quad w_0 = 90 \quad \bar{S} = 500 \quad I_0 = 0$ $\omega_2 = .2 \quad w_i \geq 75 \quad S_0 = 300 \quad \text{Total cost} = 170,102.51$					
<u>t=6</u>					
Time	Work	Production	Inventory	Reliability	Probability
t	Force	level	level		level
	$w_t$	$p_t$	$I_t$	$y_t$	$u_t$
1	83	438.630	320.007	.69315023	.5
2	77	307.060	320.007	1.6353335	.805
3	75	297.253	320.007	1.5863018	.795
4	75	297.253	320.007	1.5863018	.795
5	75	297.253	320.007	1.5863018	.795
6	75	297.253	320.000	1.5863018	.795

Table 4.1.5. Optimal solutions of the quadratic program (exponential reliability)

$\omega_1 = .8$ $w_0 = 90$ $\bar{S} = 500$ $I_0 = 0$ $\omega_2 = .2$ $w_i \geq 75$ $S_0 = 250$ Total cost = 158,605.83					
<u>t=6</u>					
Time	Work Force	Production level	Inventory level	Reliability	Probability level
t	$w_t$	$p_t$	$I_t$	$y_t$	$u_t$
1	82	335.367	320.006	1.6214675	.803
2	76	303.832	320.006	1.4953506	.776
3	75	297.253	320.006	1.4690329	.760
4	75	297.253	320.006	1.4690329	.760
5	75	297.253	320.006	1.4690329	.760
6	75	297.253	320.000	1.4690329	.760

Table 4.1.6. Optimal solutions of the quadratic program (exponential reliability)

$\omega_1 = .8$ $w_0 = 75$ $\bar{S} = 1100$ $I_0 = 320$ $\omega_2 = .2$ $w_i \geq 75$ $S_0 = 800$ Total cost = 430,435.26					
<u>t=6</u>					
Time	Work Force	Production level	Inventory level	Reliability	Probability level
t	$w_t$	$p_t$	$I_t$	$y_t$	$u_t$
1	77	687.945	596.598	.69315023	.5
2	75	411.347	596.598	.69315023	.5
3	75	411.347	596.598	.69315023	.5
4	75	411.347	596.598	.69315023	.5
5	75	411.345	596.598	.69315023	.5
6	75	411.345	596.598	.69315023	.5

Table 4.1.7. Optimal solutions of the quadratic program  
(exponential reliability)

$t=6$					
$\omega_1 = .8 \quad w_0 = 90 \quad \bar{S} = 500 \quad I_0 = 0$					
$\omega_2 = .2 \quad w_i \geq 75 \quad S_0 = 300 \quad \text{Total cost} = 170,102.51$					
Time $t$	Work Force $w_t$	Production level $p_t$	Inventory level $I_t$	Reliability $y_t$	Probability level $u_t$
1	83	438.630	320.007	.69315023	.5
2	77	307.059	320.007	1.6353335	.805
3	75	297.253	320.007	1.5863018	.795
4	75	297.253	320.007	1.5863018	.795
5	75	297.253	320.007	1.5863018	.795
6	75	297.253	320.000	1.5863018	.795

Table 4.1.8. Optimal solutions of the quadratic program  
(exponential reliability)

$t=6$					
$\omega_1 = .8 \quad w_0 = 90 \quad \bar{S} = 500 \quad I_0 = 160$					
$\omega_2 = .2 \quad w_i \geq 75 \quad S_0 = 300 \quad \text{Total cost} = 158,606.16$					
Time $t$	Work Force $w_t$	Production level $p_t$	Inventory level $I_t$	Reliability $y_t$	Probability level $u_t$
1	82	335.367	320.007	.97683777	.623
2	76	303.833	320.007	1.6191993	.802
3	75	297.253	320.007	1.5863018	.795
4	75	297.253	320.007	1.5863018	.795
5	75	297.253	320.007	1.5863018	.795
6	75	297.253	320.007	1.5863018	.795

Table 4.1.9. Optimal solutions of the quadratic program  
(exponential reliability)

$\omega_1 = .8 \quad w_0 = 90 \quad \bar{S} = 500 \quad I_0 = 480$ $\omega_2 = .2 \quad w_i \geq 75 \quad S_0 = 300 \quad \text{Total cost} = 158,606.16$					
Time $t$	Work Force $w_t$	Production level $p_t$	Inventory level $I_t$	Reliability $Y_t$	Probability level $u_t$
1	82	335.368	320.01	2.57683	.924
2	76	303.832	320.01	1.619199	.802
3	75	297.253	320.01	1.586302	.795
4	75	297.253	320.01	1.586302	.795
5	75	297.253	320.01	1.586302	.795
6	75	297.253	320.00	1.586302	.795

Table 4.1.10. Optimal solutions of the quadratic program  
(exponential reliability)

$\omega_1 = .8 \quad w_0 = 90 \quad \bar{S} = 500 \quad I_0 = 320$ $\omega_2 = .2 \quad w_i \geq 75 \quad S_0 = 300 \quad \text{Total cost} = 158,606.16$					
Time $t$	Work Force $w_t$	Production level $p_t$	Inventory level $I_t$	Reliability $Y_t$	Probability level $u_t$
1	82	335.368	320.01	1.776838	.831
2	76	303.833	320.01	1.619199	.802
3	75	297.253	320.01	1.586302	.795
4	75	297.253	320.01	1.586302	.795
5	75	297.253	320.01	1.586302	.795
6	75	297.253	320.00	1.586302	.795

size is 320.0 gallons. That is when the expression  $c_7(I_0 - c_8)$  will be equal to zero. Then for an initial inventory of zero the probability to achieve the production planning in the first period is very low i.e., 50% while for  $I_0$  equal to 160 it is 62.3% in the same period, while for  $I_0$  equal to 320, the probability rises to 83.1% and if we had an initial inventory equal to 480 the probability level for the first period will be 92.4%. We can observe in Tables 4.1.7, 4.1.8, 4.1.9, and 4.1.10 that our planning variables are almost insensitive for planning periods other than the first period.

Since the Lagrange multipliers are almost the same in most cases we only present in Table 4.1.11 those associated with the solution indicated in Table 4.1.10.

Table 4.1.11. Lagrange multipliers associated with the solution in Table 4.1.10

Code	Restriction	Value
R127	labor force in 3rd period	333.4237
R128	labor force in 4th period	452.8061
R129	labor force in 5th period	452.8061
R130	labor force in 6th period	452.8061
R131	production in 1st period	0.000999
R134	production in 4th period	0.000999
R135	production in 5th period	0.000999
R136	production in 6th period	0.000999

We see in Table 4.1.11 that the most binding restrictions are the labor force in periods 4, 5, and 6.

#### 4.1.2. Comparison with chance constrained programming

We have seen in section 4.1.1 a system reliability model for production planning, here we will have a quadratic programming problem with chance constraints which develops a method of providing appropriate safety margin under chance constraints, by incorporating the distributional characteristics of the random variables of the problem e.g., the sale vector in our production planning model. In this method a tolerance level, in terms of probability measure, one for which probability constraint is preassigned by us and this set of tolerance is supposed to indicate the limit up to which constraint violations are permitted by our satisfying behavior.

If we assume that sales have an exponential distribution as

$$f(S; \mu, S_0) = \mu e^{-\mu(S-S_0)}$$

then our restriction

$$\text{Prob} (p_t + I_{t-1} \geq S_t) \geq u_t$$

will be

$$\text{Prob}(S_t \leq p_t + I_{t-1}) \geq u_t$$

$$F(t) = \text{Prob}(S \leq t) = 1 - e^{-\mu(t-S_0)}$$

$$R(t) = 1 - F(t) = e^{-\mu(t-S_0)}$$

Therefore

$$\text{Prob}(S_t \leq p_t + I_{t-1}) \geq u_t$$

$$1 - R(p_t + I_{t-1}) \geq u_t$$

$$1 - u_t \geq e^{-\mu(p_t + I_{t-1} - S_0)}$$

taking logarithm

$$\ln(1 - u_t) \geq -\mu(p_t + I_{t-1} - S_0)$$

then

$$p_t + I_{t-1} - S_0 \geq -\frac{1}{\mu} \ln(1 - u_t)$$

$$p_t + I_{t-1} \geq S_0 - \frac{1}{\mu} \ln(1 - u_t)$$

or

$$p_t + I_{t-1} \geq S_0 - \lambda \ln(1 - u_t)$$

Now, we must instead preassign a value for  $u_t$ , whereas we had before defined  $\ln(1 - u_t) = -y_t$  as a new variable. We have solved several problems for  $u_t$  equal to .85, .90, .95 and .99. The results are in Tables 4.1.12, 4.1.13, 4.1.14, 4.1.15, 4.1.16, 4.1.17, and 4.1.18. The production variable is more sensitive to the increase in the assigned value of  $u_t$  and initial inventory.



Table 4.1.12. Optimal solution of chance constrained programming models

$t=6$					
	$\omega_1 = .8$	$w_0 = 90$	$\bar{S} = 500$	$I_0 = 0$	
	$\omega_2 = .2$	$w_i \geq 75$	$S_0 = 300$	Total cost = 401,949.88	
Time $t$	Work Force $w_t$	Production level $p_t$	Inventory level $I_t$	Reliability $Y_t$	Probability level $u_t$
1	89	899.146	494.957	2.9957296	.95
2	81	404.189	513.277	2.9957296	.95
3	77	385.870	519.572	2.9957296	.95
4	75	379.574	519.572	2.9957296	.95
5	75	379.574	519.572	2.9957296	.95
6	75	379.574	320.000	2.9957296	.95

Table 4.1.13. Optimal solution of chance constrained programming models

$t=6$					
	$\omega_1 = .8$	$w_0 = 90$	$\bar{S} = 500$	$I_0 = 0$	
	$\omega_2 = .2$	$w_i \geq 75$	$S_0 = 300$	Total cost = 237,309.42	
Time $t$	Work Force $w_t$	Production level $p_t$	Inventory level $I_t$	Reliability $Y_t$	Probability level $u_t$
1	86	679.423	351.151	1.8971202	.85
2	78	328.274	364.017	1.8971202	.85
3	75	315.407	364.017	1.8971202	.85
4	75	315.407	364.017	1.8971202	.85
5	75	315.407	364.017	1.8971202	.85
6	75	315.407	320.000	1.8971202	.85

Table 4.1.14. Optimal solution of chance constrained programming models

<u>t=6</u>					
	$\omega_1 = .8$	$w_0 = 90$	$\bar{S} = 500$	$I_0 = 320$	
	$\omega_2 = .2$	$w_i \geq 75$	$S_0 = 300$	Total cost = 280,226.71	
Time t	Work Force $w_t$	Production level $p_t$	Inventory level $I_t$	Reliability $y_t$	Probability level $u_t$
1	85	579.146	505.132	2.9957296	.95
2	79	394.013	518.291	2.9957296	.95
3	75	380.855	519.572	2.9957296	.95
4	75	379.574	519.572	2.9957296	.95
5	75	379.574	519.572	2.9957296	.95
6	75	379.574	519.572	2.9957296	.95

Table 4.1.15. Optimal solution of chance constrained programming models

<u>t=6</u>					
	$\omega_1 = .8$	$w_0 = 90$	$\bar{S} = 500$	$I_0 = 160$	
	$\omega_2 = .2$	$w_i \geq 75$	$S_0 = 300$	Total cost = 331,554.89	
Time t	Work Force $w_t$	Production level $p_t$	Inventory level $I_t$	Reliability $y_t$	Probability level $u_t$
1	87	739.146	500.450	2.9957296	.95
2	80	399.101	515.784	2.9957296	.95
3	76	383.362	519.572	2.9957296	.95
4	75	379.574	519.572	2.9957296	.95
5	75	379.574	519.572	2.9957296	.95
6	75	379.574	320.000	2.9957296	.95

Table 4.1.16. Optimal solution of chance constrained programming models

$\omega_1 = .8 \quad w_0 = 90 \quad \bar{S} = 500 \quad I_0 = 320$ $\omega_2 = .2 \quad w_i \geq 75 \quad S_0 = 300 \quad \text{Total cost} = 170,398.61$					
<u>t=6</u>					
Time	Work Force	Production level	Inventory level	Reliability	Probability level
t	$w_t$	$p_t$	$I_t$	$y_t$	$u_t$
1	82	359.424	358.097	1.8971202	.85
2	77	321.327	364.017	1.8971202	.85
3	75	315.407	364.017	1.8971202	.85
4	75	315.407	364.017	1.8971202	.85
5	75	315.407	364.017	1.8971202	.85
6	75	315.407	364.017	1.8971202	.85

Table 4.1.17. Optimal solution of chance constrained programming models

$\omega_1 = .8 \quad w_0 = 90 \quad \bar{S} = 500 \quad I_0 = 320$ $\omega_2 = .2 \quad w_i \geq 75 \quad S_0 = 300 \quad \text{Total cost} = 612,406.18$					
<u>t=6</u>					
Time	Work Force	Production level	Inventory level	Reliability	Probability level
t	$w_t$	$p_t$	$I_t$	$y_t$	$u_t$
1	90	901.034	709.713	4.60517	.99
2	84	511.321	727.490	4.60517	.99
3	80	493.544	739.499	4.60517	.99
4	77	481.535	746.091	4.60517	.99
5	75	474.943	747.458	4.60517	.99
6	75	473.576	320.000	4.60517	.99

Table 4.1.18. Optimal solution of chance-constrained programming models

<hr/>					
<u>t=6</u>	$\omega_1 = .8$	$w_0 = 90$	$\bar{S} = 500$	$I_0 = 320$	
	$\omega_2 = .2$	$w_1 \geq 75$	$S_0 = 300$	Total cost = 199,980.58	
Time t	Work Force $w_t$	Production level $p_t$	Inventory level $I_t$	Reliability level $y_t$	Probability level $u_t$
1	83	440.518	412.669	2.3029995	.90
2	77	347.850	421.429	2.3029995	.90
3	75	339.090	421.429	2.3029995	.90
4	75	339.090	421.429	2.3029995	.90
5	75	339.090	421.429	2.3029995	.90
6	75	339.090	421.429	2.3029995	.90
<hr/>					

If we assume that sales are normally and independently distributed as

$$f(S; m, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(S-m)^2}{2\sigma^2}}$$

Then our restriction

$$\text{Prob}(p_t + I_{t-1} \geq S_t) \geq u_t$$

will be transforms as

$$\text{Prob}(S_t \leq p_t + I_{t-1}) \geq u_t$$

$$\text{Prob}\left(\frac{S_t - m}{\sqrt{\sigma^2}} \leq \frac{p_t + I_{t-1} - m}{\sqrt{\sigma^2}}\right) \geq u_t$$

Then

$$F\left(\frac{p_t + I_{t-1} - m}{\sqrt{\sigma^2}}\right) \geq u_t$$

and

$$\frac{p_t + I_{t-1} - m}{\sqrt{\sigma^2}} \geq F^{-1}(u_t)$$

finally

$$p_t + I_{t-1} - m \geq \sigma F^{-1}(u_t)$$

$$p_t + I_{t-1} \geq m + \sigma F^{-1}(u_t)$$

When a normal distribution is assumed for the sales the mean  $\mu$  and standard deviation  $\sigma$  are sufficient to fully determine the distribution function. As we have used in our earlier problems an exponential distribution with two parameters, we have the following estimates of the normal parameters  $m$  and  $S$  on the basis of our earlier results.

$$\mu^{-1} = S$$

$$\mu^{-1} = \bar{S}_t - S_0$$

$$S = 500 - 300 = 200$$

$$S_0 = m - S$$

then

$$m = S_0 + S$$

$$m = 300 + 200 = 500$$

In Table 4.1.19 we assume that  $F^{-1}(u_t) = -1.65$  that is the value of  $u_t$  is equal to 95%. If we compare these results with those given in Table 4.1.14 we observe that the normal assumption gives us lower results than the exponential distribution. This is because the exponential distribution gives higher ordinate values at lower abscissa values.

In Figure 4.1.5 we show a curve of substitution between cost and system reliability for several exponential CCP cases.

Table 4.1.19. Optimal solution of chance-constrained programming model (Normal case)

<hr/>					
<u>t=6</u>	$\omega_1 = 1$	$w_0 = 90$	$\bar{m} = 500$	$I_0 = 320$	
	$\omega_2 = 0$	$w_i \geq 75$	$S = 200$	Total cost = 265,766.81	
Time	Work Force	Production level	Inventory level	Reliability	Probability level
t	$w_t$	$p_t$	$I_t$	$y_t$	$u_t$
1	82	335.36	320	1.65	.95
2	76	303.83	320	1.65	.95
3	75	297.25	320	1.65	.95
4	75	297.25	320	1.65	.95
5	75	297.25	320	1.65	.95
6	75	297.25	320	1.65	.95
<hr/>					

Finally in Table 4.1.20 we have shown the Lagrange multipliers associated with the solution in Table 4.1.12 which indicates the most binding restriction to be the lower bound reliability for the first period.

Table 4.1.20. Lagrange multipliers associated with the solution in Table 4.1.12

Code	Restrictions	Value
R128	labor force in 4th period	142.0903
R129	labor force in 5th period	303.4436
R130	labor force in 6th period	303.4436
R131	production in 1st period	167.5241
R132	production in 2nd period	23.0944
R133	production in 3rd period	25.5126
R134	production in 4th period	26.3436
R135	production in 5th period	26.3436
R136	production in 6th period	26.3436
R137	lower bound reliability for the 1st period	33504.626
R138	lower bound reliability for the 2nd period	4618.6862
R139	lower bound reliability for the 3rd period	5102.3152
R140	lower bound reliability for the 4th period	5268.5210
R141	lower bound reliability for the 5th period	5268.5210
R142	lower bound reliability for the 6th period	5268.5210

#### 4.2. Application of Multi-Period Investment under Uncertainty: Implication of Decisions Rules

Näslund (89, 90) considered a model of rational investment in the stock market. The model itself abstracts from a more general problem of resource carryover under risk. He assumes that a person has a known income stream. Furthermore, he assumes that a person has decided how to allocate his consumption up to a specified horizon. Each period the difference between income and consumption is made available for investment in the stock market. His goal is the

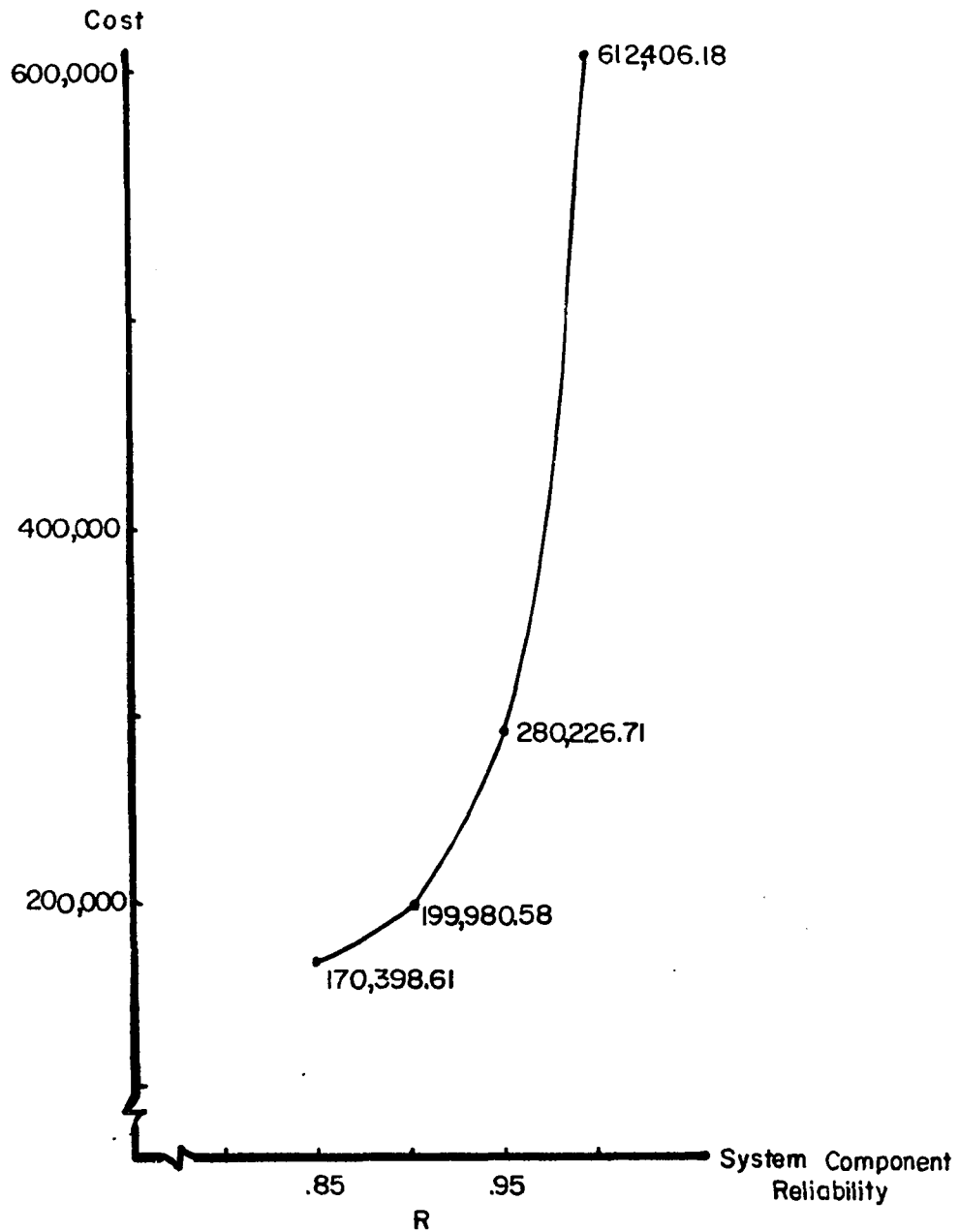


Figure 4.1.5. Curve of Substitution between Cost and System Component Reliability. CCP (2 Parameter - Exponential)



maximization of his expected gain in the stock market at the end of the specified horizon subject to certain constraints in each period. Such as: the risk constraint which in effect sets a probabilistic limit on possible losses beyond a specified amount; and a capital constraint which probabilistically stipulates that invested capital should be below a limit which varies according to accumulated capital gains. Näslund assumes that the investor is not affected in his risk aversion by the actual outcomes of his investments.

The problem is formulated in the following way

$$\text{Max } E\left\{ \sum_{i=1}^n x_i \frac{p_i - p_{i-1}}{p_{i-1}} \right\} \quad [4.2.1]$$

subject to

$$\text{Prob} \left\{ x_i \frac{p_i - p_{i-1}}{p_{i-1}} \geq L_i \right\} \geq \alpha_i$$

$$\text{Prob} \left\{ x_i \leq k_i + \sum_{j=2}^i x_{j-1} \frac{p_{j-1} - p_{j-2}}{p_{j-2}} \right\} \geq \eta_i$$

where

$x_i$  is the accumulated amount in dollars invested in stocks

$p_i$  is the stock price or group of stocks price in period  $i$

$L_i$  is the maximum loss that the person is willing to take in period  $i$

$\alpha_i$  is the risk prescribed for period  $i$

$k_i$  is the capital accumulated that the person can use for investment either in cash or stocks apart from the returns on earlier investments

$\eta_i$  is the risk level for capital constraint in period  $i$

It is assumed that  $(p_i - p_{i-1})/p_{i-1}$  is approximately normally distributed. Osborne has made such assumptions in (92).

In solving the above model Näslund pointed out that consideration must be given to the fact that certain data which are presently unavailable i.e., the stock prices, will be varying in the future, when actual decisions are made. For this reason he does not solve directly for the  $x$ 's, but a decision rule of the following form

$$x_i = \sum_{j=2}^i \beta_j \left[ 1 + \frac{p_{j-1} - p_{j-2}}{p_{j-2}} \right] + \gamma_i \quad [4.2.2]$$

is introduced in the model replacing  $x_i$  and he had to determine as a solution  $\beta$ 's and  $\gamma$ 's. Since  $x_k$  in period  $k$  is a function of known past prices at that time, the decision rule can be interpreted as the demand of a particular person to hold funds inverted in the stock market.

Näslund only considers a three year horizon in order to limit the numerical calculation. We will consider the same case and data in order to compare our results with his.

Therefore the problem can then be written as:

$$\begin{aligned} \text{Max } E\{ & \gamma_1 \frac{p_1 - p_0}{p_0} + [\beta_2 (1 + \frac{p_1 - p_0}{p_0}) + \gamma_2] \frac{p_2 - p_1}{p_1} \\ & + [\beta_3 (1 + \frac{p_2 - p_1}{p_1}) + \gamma_3] \frac{p_3 - p_2}{p_2} \} \end{aligned}$$

subject to loss constraints i.e., the maximum loss that the person is willing to take in period i

$$\text{Prob } (\gamma_1 \frac{p_1 - p_0}{p_0} \geq L_1) \geq \alpha_1$$

$$\text{Prob } \{ [\beta_2 (1 + \frac{p_1 - p_0}{p_0}) + \gamma_2] \frac{p_2 - p_1}{p_1} \geq L_2 \} \geq \alpha_2$$

$$\text{Prob } \{ [\beta_3 (1 + \frac{p_2 - p_1}{p_1}) + \gamma_3] \frac{p_3 - p_2}{p_2} \geq L_3 \} \geq \alpha_3$$

Capital constraints i.e. the capital accumulated that the person can use for investment either in cash or stocks apart from the return on early investment

$$\gamma_j \leq k_1$$

$$\text{Prob } \{ \beta_2 [1 + \frac{p_1 - p_0}{p_0}] + \gamma_2 \leq k_2 + \gamma_1 \frac{p_1 - p_0}{p_0} \geq \eta_2$$

$$\begin{aligned} \text{Prob } \{ \beta_3 [1 + \frac{p_2 - p_1}{p_1}] + \gamma_3 \leq k_3 + \gamma_1 \frac{p_1 - p_0}{p_0} \\ + [\beta_2 (1 + \frac{p_1 - p_0}{p_0}) + \gamma_2] \frac{p_2 - p_1}{p_1} \geq \eta_3 \} \end{aligned}$$

In order to solve numerically, Näslund assigned the following values to the parameters

$$L_1 = -1300 \text{ (dollars)}$$

$$L_2 = -1000$$

$$L_3 = -1000$$

$$\alpha_1 = \alpha_2 = \alpha_3 = 95\%$$

$$k_1 = 7000 \text{ (dollars)}$$

$$k_2 = 5500$$

$$k_3 = 9000$$

$$\eta_2 = 99.997\%$$

$$\eta_3 = 99\%$$

$$\mu = 0.05, \text{ mean of the distribution of } (p_i - p_{i-1})/p_{i-1}$$

$$\sigma = 0.15, \text{ standard deviation of the distribution of } (p_i - p_{i-1})/p_{i-1}$$

He inserts these values in the constraints and considers  $[(p_j - p_{j-1})/p_{j-1}]^n$  small for  $n \geq 2$ .

The deterministic equivalents to the probabilistic constraints are derived by methods indicated before.

He uses the following property of normal variates

$$\text{Prob } \{y \geq Q\} = \frac{1}{\sqrt{2\pi}} \int_{(Q-\mu)/\sigma}^{\infty} \exp(-y^2/2) dy = \frac{1}{2} - F\left(\frac{Q-\mu}{\sigma}\right)$$

where  $F(x)$  is the normal function

$$F(x) = \frac{1}{\sqrt{2\pi}} \int_0^x \exp(-y^2/2) dy$$

Therefore the constraints can be written as follows

$$\frac{1}{2} - F\left(\frac{-1300-0.05 \gamma_1}{0.15 \gamma_1}\right) \geq 0.95$$

$$\frac{1}{2} - F\left(\frac{-1000-0.05(\beta_2+\gamma_2)}{0.15(\beta_2+\gamma_2)}\right) \geq 0.95$$

$$\frac{1}{2} - F\left(\frac{-1000-0.05(\beta_3+\gamma_3)}{0.15(\beta_3+\gamma_3)}\right) \geq 0.95$$

$$\gamma_1 \leq 7000$$

$$\frac{1}{2} - F\left(\frac{\beta_2+\gamma_2-5500-0.05(\gamma_1-\beta_2)}{0.15(\gamma_1-\beta_2)}\right) \geq 0.9997$$

$$\frac{1}{2} - F\left(\frac{\beta_3+\gamma_3-9000-0.05(\gamma_1+\beta_2+\gamma_2-\beta_3)}{0.15\sqrt{(\beta_2+\gamma_2-\beta_3)^2+\gamma_1^2}}\right) \geq 0.99$$

If we rearrange the equations we get

$$F\left(\frac{1300+0.05 \gamma_1}{0.15 \gamma_1}\right) \geq 0.45$$

$$F\left(\frac{1000+0.05(\beta_2+\gamma_2)}{0.15(\beta_2+\gamma_2)}\right) \leq 0.45$$

$$\gamma_1 \leq 7000$$

$$F\left(\frac{5500+0.05(\gamma_1-\beta_2)-\beta_2-\gamma_2}{0.15(\gamma_1-\beta_2)}\right) \geq 0.49997$$

$$F\left(\frac{9000.+0.05(\gamma_1+\beta_2+\gamma_2-\beta_3)-\beta_3-\gamma_3}{0.15\sqrt{(\beta_2+\gamma_2-\beta_3)^2+\gamma_1^2}}\right) \geq 0.49$$

Using the transformation that if  $z=F(y)$  then  $y=F^{-1}(z)$  we get

$$\frac{1300+0.05 \gamma_1}{0.15 \gamma_1} \geq F^{-1}(0.45) \equiv 1.65$$

$$\frac{1000+0.05(\beta_2+\gamma_2)}{0.15(\beta_2+\gamma_2)} \geq F^{-1}(0.45) \equiv 1.65$$

$$\frac{1000+0.05(\beta_3+\gamma_3)}{0.15(\beta_3+\gamma_3)} \geq F^{-1}(0.45) \equiv 1.65$$

$$\gamma_1 \leq 7000$$

$$\frac{5500+0.05 \gamma_1-1.05 \beta_2+\gamma_2}{0.15(\gamma_1-\beta_2)} \geq F^{-1}(0.49997) \equiv 4.0$$

$$\frac{9000+0.05(\gamma_1+\beta_2+\gamma_2)-1.05 \beta_3-\gamma_3}{0.15\sqrt{(\beta_2+\gamma_2-\beta_3)^2+\gamma_1^2}} \geq F^{-1}(0.49) \equiv 2.33$$

Once again if we rearrange the constraints above, the problem takes the following form.

$$\text{Max } E\left\{ \sum_{i=1}^n x_i \frac{p_i - p_{i-1}}{p_{i-1}} \right\}$$

subject to

$$\begin{aligned}
\gamma_1 &\leq 6500 \\
\gamma_2 + \beta_2 &\leq 5000 \\
\gamma_3 + \beta_3 &\leq 5000 \\
0.55 \gamma_1 + 0.45 \beta_2 + \gamma_2 &\leq 5500 \\
0.35 \sqrt{(\beta_2 + \gamma_2 - \beta_3)^2 + \gamma_1^2} + 1.05 \beta_3 + \gamma_3 - 0.05(\gamma_1 + \beta_2 + \gamma_2) &\leq 9000
\end{aligned}$$

The reason that we have only five constraints here, is because it turns out that  $\gamma_1 \leq 6500$  dominates  $\gamma_1 \leq 7000$  in the sense that it is more constraining. Here we have a major departure from Näslund, because he neglects the last restriction and solves only the linear part of the problem, e.g. Näslund solves only a linear programming problem. We solve instead the nonlinear programming problem and in Table 4.2.1 we can see the difference in solutions we got

Table 4.2.1. Decision rule solutions

Variable	Linear solution (LP model)	Nonlinear solution (NLP model)
$\gamma_1$	5900	5909.1632
$\gamma_2$	0	0.21259
$\gamma_3$	5000	2696.9716
$\beta_2$	5000	4999.0663
$\beta_3$	0	2302.8111

For solving the nonlinear solution we have used SUMT (sequential unconstrained minimization technique) (51, 126, 52, 53, 49, 48, 17, 50, 82). According to the decision rule given in (4.2.2) we have the following form of investment decisions where  $x_j$  denotes the total amount of money held in stocks in period  $j$ .

$$x_1 = \gamma_1 \quad [4.2.3]$$

$$x_2 = \beta_2 \left(1 + \frac{p_1 - p_0}{p_0}\right) + \gamma_2 \quad [4.2.4]$$

$$x_3 = \beta_3 \left(1 + \frac{p_2 - p_1}{p_1}\right) + \gamma_3 \quad [4.2.5]$$

Now if we insert the value of Table 4.2.1 in equations 4.2.3, 4.2.4, 4.2.5 we have

Linear solution

$$\begin{aligned} x_1 &= 5900 \\ x_2 &= 5000 \left(1 + \frac{p_1 - p_0}{p_0}\right) \\ x_3 &= 5000 \end{aligned}$$

Nonlinear solution

$$\begin{aligned} x_1 &= 5909.1632 \\ x_2 &= 4999.0663 \left(1 + \frac{p_1 - p_0}{p_0}\right) + 0.21259 \\ x_3 &= 2302.8111 \left(1 + \frac{p_2 - p_1}{p_2}\right) + 2696.9716 \end{aligned}$$

We can see that solving a nonlinear programming



formulation gives us a slightly different problem; the decisions that explicitly depend on the random variable  $\frac{p_{j-1}-p_{j-2}}{p_{j-2}}$  are the decisions in the second and third period while in linear formulation the random variable is important only in the second period. In Table 4.2.2 we compare the problems for a price increase of 5% or 10% between period 0 to 1 and 1 to 2.

Table 4.2.2. Price variation in decision rules<sup>a</sup>

Variable	Linear solution		Nonlinear solution	
	5%	10%	5%	10%
$x_1$	5900	5900	5909.16	5909.16
$x_2$	5250	5500	5249.23	5499.19
$x_3$	5000	5000	5114.92	5230.06
$z^b$	807.5	820.0	813.67	831.92

<sup>a</sup>These values are rounded.

<sup>b</sup> $z$  denotes the value of the objective function of problem [4.2.1].

We can observe that there exists more variability in the value of the objective function of the nonlinear formulation due to changes in the random variable  $\frac{p_{j-1}-p_{j-2}}{p_{j-2}}$ .

If we do not want to use a decision rule as given in Equation [4.2.2], then we solve an optimization problem in nonlinear programming. We have then the following problem:

$$\text{Max } E(x_1 \frac{p_1 - p_0}{p_0} + x_2 \frac{p_2 - p_1}{p_1} + x_3 \frac{p_3 - p_2}{p_2}) \quad [4.2.6]$$

subject to

$$\text{Prob}(x_1 \frac{p_1 - p_0}{p_0} \geq -1300) \geq .95 \quad [4.2.7]$$

$$\text{Prob}(x_2 \frac{p_2 - p_1}{p_1} \geq -1000) \geq .95 \quad [4.2.8]$$

$$\text{Prob}(x_3 \frac{p_3 - p_2}{p_2} \geq -1000) \geq .95 \quad [4.2.9]$$

$$x_1 \leq 7000$$

$$\text{Prob}(x_2 \leq 5500 + x_1 \frac{p_1 - p_0}{p_0}) \geq .99997 \quad [4.2.10]$$

$$\text{Prob}(x_3 \leq 9000 + x_1 \frac{p_1 - p_0}{p_1} + x_2 \frac{p_2 - p_1}{p_1}) \geq .99 \quad [4.2.11]$$

as we know  $\frac{p_i - p_{i-1}}{p_{i-1}}$  is normal and independently distributed

with mean  $\mu = .05$  and standard deviation  $\sigma = .15$ . Therefore

the objective function [4.2.6] will be

$$\text{Max } .05 x_1 + .05 x_2 + .95 x_3 \quad [4.2.12]$$

For restriction [4.2.7], [4.2.8] and [4.2.9] we can make

the following simplifications:

The probabilities in those restrictions can then be

transformed by simple subtraction and division as follows.

For restriction [4.2.7]

$$\text{Prob}\left(\frac{x_i \frac{p_i - p_{i-1}}{p_{i-1}} - \mu x_i}{\sqrt{\sigma^2 x_i^2}} \geq \frac{L_i - \mu x_i}{\sqrt{\sigma^2 x_i^2}}\right) \geq \alpha \quad [4.2.13]$$

The left hand side of the argument of the probability expression is found to be a normalized random variable with zero mean and unit variance. Hence the probabilistic condition is replaced by

$$1 - F\left(\frac{L_i - \mu x_i}{\sigma x_i}\right) \geq \alpha$$

where

$$F(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-y^2/2} dy$$

Then

$$F\left(\frac{L_i - \mu x_i}{\sigma x_i}\right) \leq 1 - \alpha$$

therefore

$$L_i - \mu x_i \geq \sigma x_i F^{-1}(1 - \alpha)$$

and

$$L_i - [\mu + \sigma F^{-1}(1 - \alpha)] x_i \geq 0 \quad [4.2.14]$$

For restriction [4.2.10] we use the notation

$$\frac{p_i - p_{i-1}}{p_{i-1}} \equiv \beta_i \text{ and } \bar{\beta}_i = E\left(\frac{p_i - p_{i-1}}{p_{i-1}}\right), \sigma_{\beta_i}^2 = \text{Var}\left(\frac{p_i - p_{i-1}}{p_{i-1}}\right) \text{ and}$$

note that

$$\text{Prob}(x_2 \leq k_2 + x_1 \beta_1) \geq \eta_2$$

which we rewrite as

$$\text{Prob}(x_1\beta_1 \geq x_2 - k_2) \geq \eta_2$$

so

$$\text{Prob}\left(\frac{x_1\beta_1 - x_1\bar{\beta}_1}{\sqrt{\sigma_{\beta_1}^2 x_1^2}} \geq \frac{x_2 - k_2 - x_1\bar{\beta}_1}{\sqrt{\sigma_{\beta_1}^2 x_1^2}}\right) \geq \eta_2$$

for the same reason given for expression [4.2.13] we have

$$1 - F\left(\frac{x_2 - k_2 - x_1\bar{\beta}_1}{\sigma_{\beta_1} x_1}\right) \geq \eta_2$$

$$F\left(\frac{-x_2 + k_2 + x_1\bar{\beta}_1}{\sigma_{\beta_1} x_1}\right) \leq 1 - \eta_2$$

and

$$-x_2 + k_2 + x_1\bar{\beta}_1 \geq F^{-1}(1 - \eta_2) \sigma_{\beta_1} x_1$$

collecting terms

$$[-\bar{\beta}_1 + \sigma_{\beta_1} F^{-1}(1 - \eta_2)] x_1 - x_2 \leq k_2 \quad [4.2.15]$$

For restriction [4.2.11] we have the same procedure as follows:

we can rewrite [4.2.11] as

$$\text{Prob}(x_1\beta_1 + x_2\beta_2 \geq x_3 - k_3) \geq \eta_3$$

so we have

$$\text{Prob}\left(\frac{x_1\beta_1+x_2\beta_2-x_1\bar{\beta}_1-x_2\bar{\beta}_2}{\sqrt{\sigma_{\beta_1}^2x_1^2+\sigma_{\beta_1}^2x_2^2}} \geq \frac{x_3-k_3-x_1\bar{\beta}_1-x_2\bar{\beta}_2}{\sqrt{\sigma_{\beta_1}^2x_1^2+\sigma_{\beta_2}^2x_2^2}}\right) \geq \eta_3$$

as we already know  $\bar{\beta}_1=\bar{\beta}_2=\bar{\beta}$  and  $\sigma_{\beta_2}^2=\sigma_{\beta_1}^2=\sigma^2$  then we have

$$1-F\left(\frac{x_3-k_3-x_1\bar{\beta}-x_2\bar{\beta}}{\sigma\sqrt{x_1^2+x_2^2}}\right) \geq \eta_3$$

$$F\left(\frac{-x_3+k_3+x_1\bar{\beta}+x_2\bar{\beta}}{\sigma\sqrt{x_1^2+x_2^2}}\right) \leq 1-\eta_3$$

therefore

$$-\bar{\beta}x_1-\bar{\beta}x_2+x_3+\sigma F^{-1}(1-\eta_3)\sqrt{x_1^2+x_2^2} \leq k_3 \quad [4.2.16]$$

Summarizing expressions [4.2.12], [4.2.14], [4.2.15],

and [4.2.16] in the form fashionable to SUMT we will have the following model:

$$\text{Max } .05 x_1 + .05 x_2 + .05 x_3 \quad [4.2.17]$$

subject to

$$\begin{array}{llll} 1300 + (.05-.15 \psi)x_1 & & & \geq 0 \\ 1000 & + (.05-.15 \psi)x_2 & & \geq 0 \\ 1000 & & + (.05-.15 \psi)x_3 & \geq 0 \\ 7000 & -x_1 & & \geq 0 \\ 5500 + (.05-.15 \psi)x_1 & & -x_2 & \geq 0 \\ -.15\phi\sqrt{x_1^2+x_2^2} + 9000 & +.05x_1 & +.05x_2 & -x_3 \geq 0 \end{array}$$

where

$$\psi = F^{-1}(\alpha - \frac{1}{2})$$

$$\Psi = F^{-1}(\eta_2 - \frac{1}{2})$$

$$\phi = F^{-1}(\eta_3 - \frac{1}{2})$$

In our case  $\psi=1.65$ ,  $\Psi=4.$ ,  $\phi=2.33$

Solving the nonlinear programming problem [4.2.17]

we have the following result

$$x_1 = 6581.36$$

$$x_2 = 3528.65$$

$$x_3 = 5024.71$$

value of objective function  $z=756.74$

Note that this optimization model has only 3 variables, while the nonlinear decision rule problem has 5 variables which make the latter model more difficult to solve in terms of programming and computing time. However in the latter model we have some flexibility of decisions in the second and third periods, while in the other case we take investment decision for three periods once and for all. Table 4.2.3 gives us a general view of our problems.

#### 4.2.1. Reliability approach

Our chance-constrained approach of a multi-period investment under uncertainty provides the basis of reliability

Table 4.2.3. Summary of problems

Decision rule problem Näslund solution (Linear programming) (1)	Optimization problem Nonlinear programming solution (2)	Decision rule problem Nonlinear solution 10% price change (3)	Decision rule problem Nonlinear solution 5% price change (4)	System reliability problem at 99%
$x_1=5900$ (783225.0) <sup>a</sup>	$x_1=6581.36$ (974571.7376)	$x_1=5909.163$ (785659.6656)	$x_1=5909.163$ (785659.6656)	$x_1=6999.975$ (1102492.1250)
$x_2=5500$ (562500.0)	$x_2=3528.65$ (280155.8435)	$x_2=5499.185$ (680423.3024)	$x_2=5249.232$ (619974.823)	$x_2=2440.3998$ (133999.9016)
$x_3=5000$ (562500.0)	$x_3=5024.71$ (568073.4882)	$x_3=5230.064$ (615455.3125)	$x_3=5114.923$ (588654.8392)	$x_3=8068.435$ (1464741.9754)
$z = 820.0$ (2026350.0)	$z = 756.74$ (1822806.0693)	$z = 831.921$ (2081538.281)	$z = 813.666$ (1994289.328)	$z = 865.3399$ (2701234.0020)
$cv^b=173.5975$	$cv=178.411$	$cv=173.4243$	$cv=173.559$	$cv=189.9304$

<sup>a</sup>Figures in parenthesis indicate variance component  $x_i^2 \sigma_i^2 / c_i^2$  at the optimal solution.

<sup>b</sup> $cv$ =Coefficient of variation defined as  $100X/\bar{x}$ .

analysis. Here we can develop an operational measure of reliability for the nonlinear programming system. In this chance-constrained problem approach a tolerance level in terms of probability measures, one for each probabilistic constraint is preassigned by the decision-maker as we saw above and this set of tolerance measures is supposed to indicate the limit up to which constraint violations are permitted. This view of chance-constraints problem allows the interpretation of our model as a system where each probability constraint can be viewed as a system component, each with its reliability in other words its tolerance measure. We develop a transformed programming model which may be specified mostly in terms of reliability measures. To form models of the form we redefine as variables for this model:

$$\begin{aligned}
 x_4 &= F^{-1}(\alpha - \frac{1}{2}) & \text{System reliability } R &= (u^*)^5 \\
 x_5 &= F^{-1}(\alpha - \frac{1}{2}) & u^* &\text{ is defined in Equation [4.2.18]} \\
 & & (1-R) &= \text{System unreliability} \\
 x_6 &= F^{-1}(\alpha - \frac{1}{2}) \\
 x_7 &= F^{-1}(\eta_2 - \frac{1}{2}) \\
 x_8 &= F^{-1}(\eta_3 - \frac{1}{2})
 \end{aligned}$$

and we incorporate an additional restriction in order to have a measure of system reliability as a whole



$$x_4 \cdot x_5 \cdot x_6 \cdot x_7 \cdot x_8 \geq (u^*)^5 \quad [4.2.18]$$

where  $u^*$  is a preassigned value. And we also add five additional constraints as upper bounds for our variables  $x_4$ ,  $x_5$ ,  $x_6$ ,  $x_7$ , and  $x_8$ . So we have

$$x_4 \leq 4.0 \quad [4.2.19]$$

$$x_5 \leq 4.0 \quad [4.2.20]$$

$$x_6 \leq 4.0 \quad [4.2.21]$$

$$x_7 \leq 4.0 \quad [4.2.22]$$

$$x_8 \leq 4.0 \quad [4.2.23]$$

The upper bound value of 4.0 corresponds in the normal curve to a value of probability 99.999999%.

Then our last step is to associate a monotonic pay-off function for achieving the level  $R$  of system reliability. As we have seen before, one possible choice of utility function satisfying conditions given in Chapter 2 is

$$\begin{aligned} \text{Max } .05x_1 + .05x_2 + .05x_3 + \ln x_4 + \ln x_5 + \ln x_6 \\ + \ln x_7 + \ln x_8 \end{aligned} \quad [4.2.24]$$

Therefore collecting the expressions [4.2.18], [4.2.19], [4.2.20], [4.2.21], [4.2.22], [4.2.23], and [4.2.24] and adding to our model [4.2.17] we got the following problem:

$$\begin{aligned} \text{Max } .05x_1 + .05x_2 + .05x_3 + \ln x_4 + \ln x_5 + \ln x_6 \\ + \ln x_7 + \ln x_8 \end{aligned}$$

subject to

$$g_1(x) \equiv 1300. + (.05 - .15x_4)x_1 \geq 0$$

$$g_2(x) \equiv 1000. + (.05 - .15x_5)x_2 \geq 0$$

$$g_3(x) \equiv 1000. + (.05 - .15x_6)x_3 \geq 0$$

$$g_4(x) \equiv 7000. - x_1 \geq 0$$

$$g_5(x) \equiv 5500. + (.05 - .15x_7)x_1 - x_2 \geq 0$$

$$g_6(x) \equiv .15x_8 \sqrt{x_1^2 + x_2^2} + 9000. + .05x_1 + .05x_2 - x_3 \geq 0$$

$$g_7(x) \equiv x_4x_5x_6x_7x_8 - (u^*)^5 \geq 0$$

$$g_8(x) \equiv 4. - x_4 \geq 0$$

$$g_9(x) \equiv 4. - x_5 \geq 0$$

$$g_{10}(x) \equiv 4. - x_6 \geq 0$$

$$g_{11}(x) \equiv 4. - x_7 \geq 0$$

$$g_{12}(x) \equiv 4. - x_8 \geq 0$$

The method for solving this specific problem using SUMT is given in Appendix B.

We have solved the following set of problems for different values of  $u^*$  such as 1.29 (90%), 1.65 (95%) and 2.33 (99%). The results are given in Table 4.2.4.

In Figure 4.2.1 we observe a substitution curve between profit and system unreliability. We have a net profit of 999.43 with 10% of system unreliability if we want to decrease system unreliability to 5% we have to trade off some net profit for it, so now we only get 923.34. Further if we want to decrease system unreliability to 1% we increase our profit to 792.35.

If we define arc elasticity of profit-reliability as

$$\epsilon_{pR} = - \frac{\frac{\partial p}{p}}{\frac{\partial R}{R}}$$

we find that the elasticity between the profit of 999.43 and 923.24 is 1.568 while the corresponding arc elasticity between the profit of 923.34 and 792.35 is 3.77.

We can find more points and give a more exact substitution curve than in Figure 4.2.1 that will show the range of choices available to the decision maker between differing levels of profit and system unreliability.

We can see in Figure 4.2.2 the changes in variable  $x_1$  due to the change in system unreliability; this variable is very sensitive that is, only the second decimal figure changes for.

In Figure 4.2.3 we can observe the changes in variable  $x_2$  due to difference in system unreliability e.g.,  $x_2$  decreases

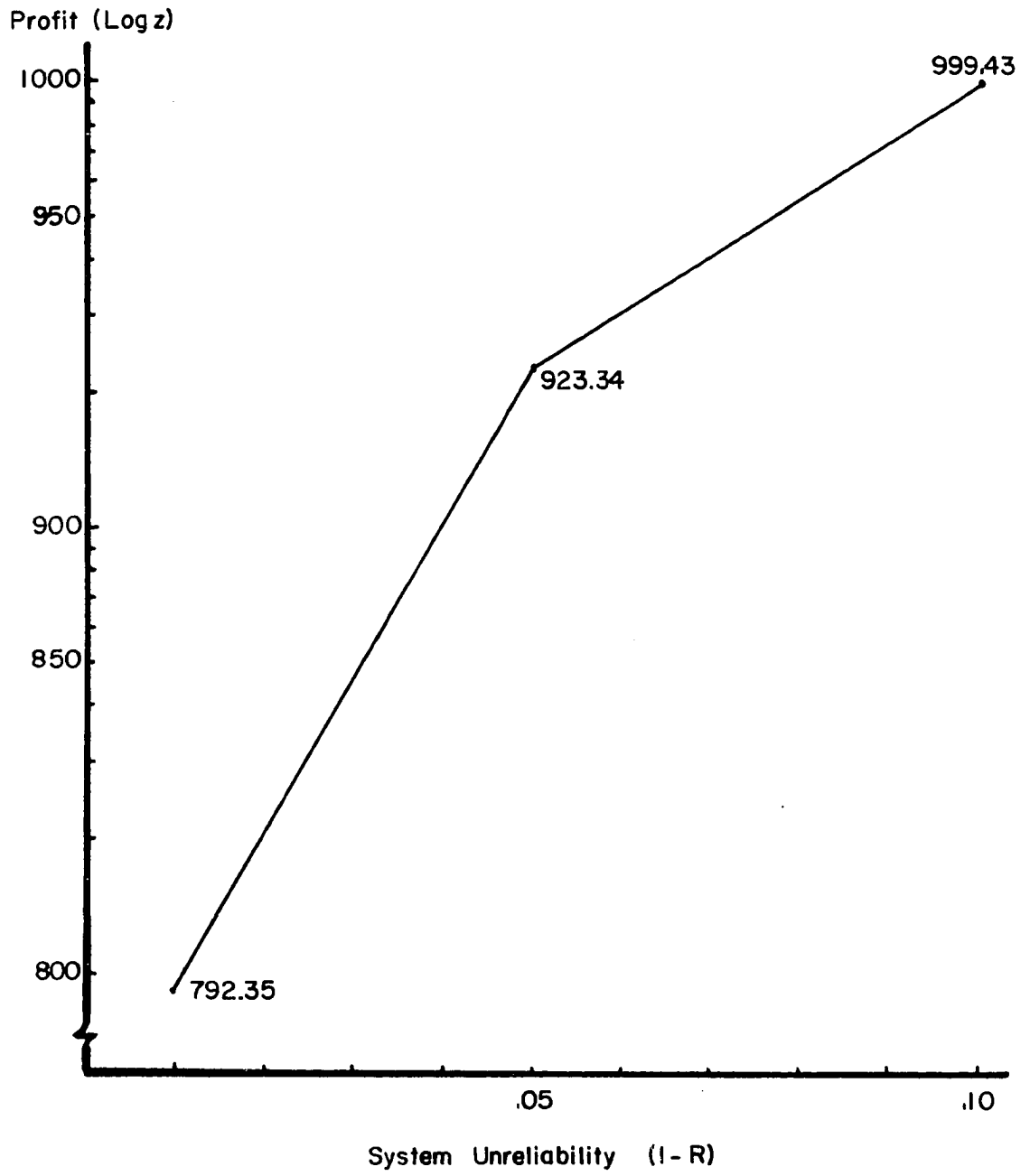


Figure 4.2.1 Substitution Curve between Profit and System Unreliability.

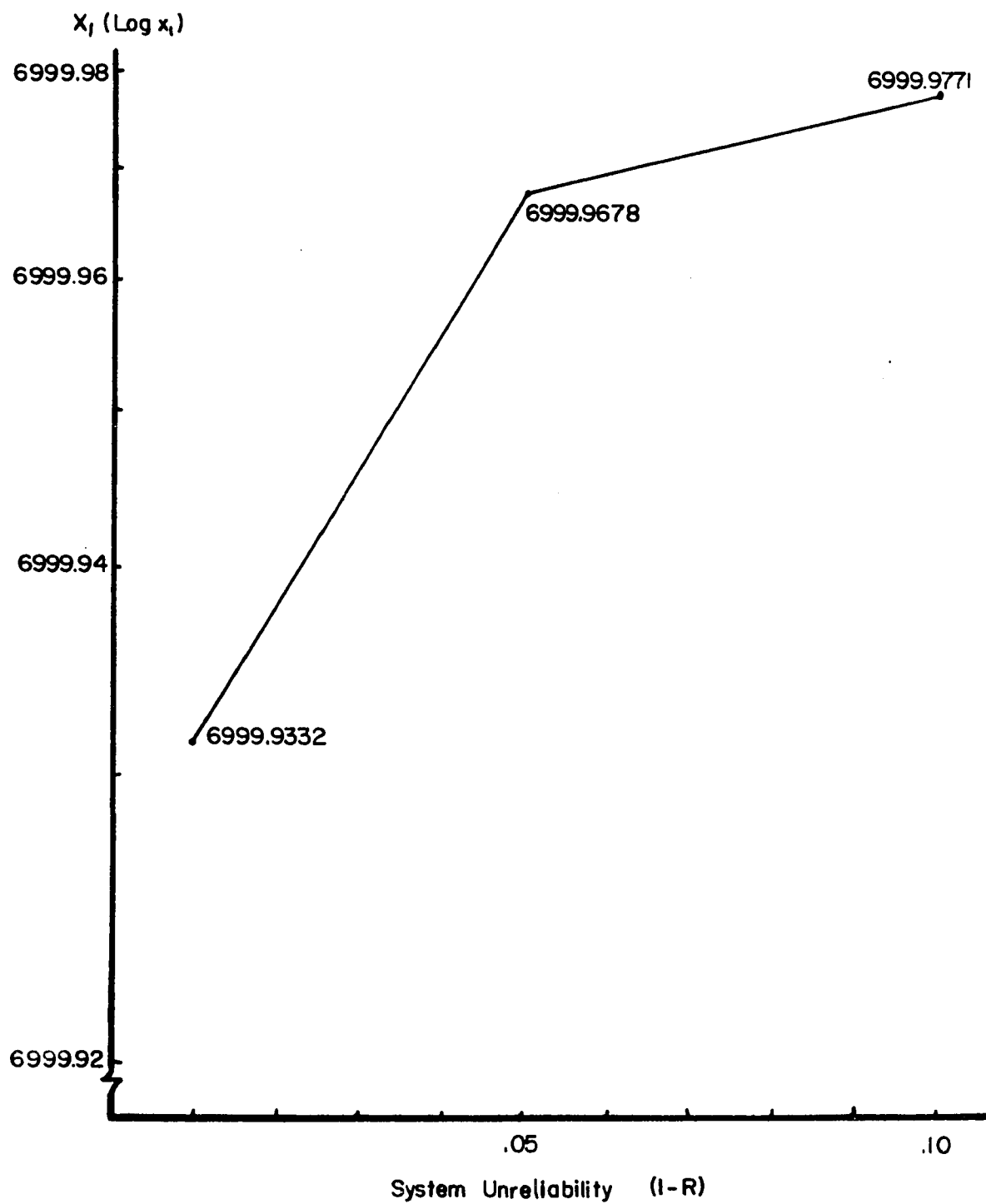


Figure 4.2.2. Curve between  $X_i$  and System Unreliability.

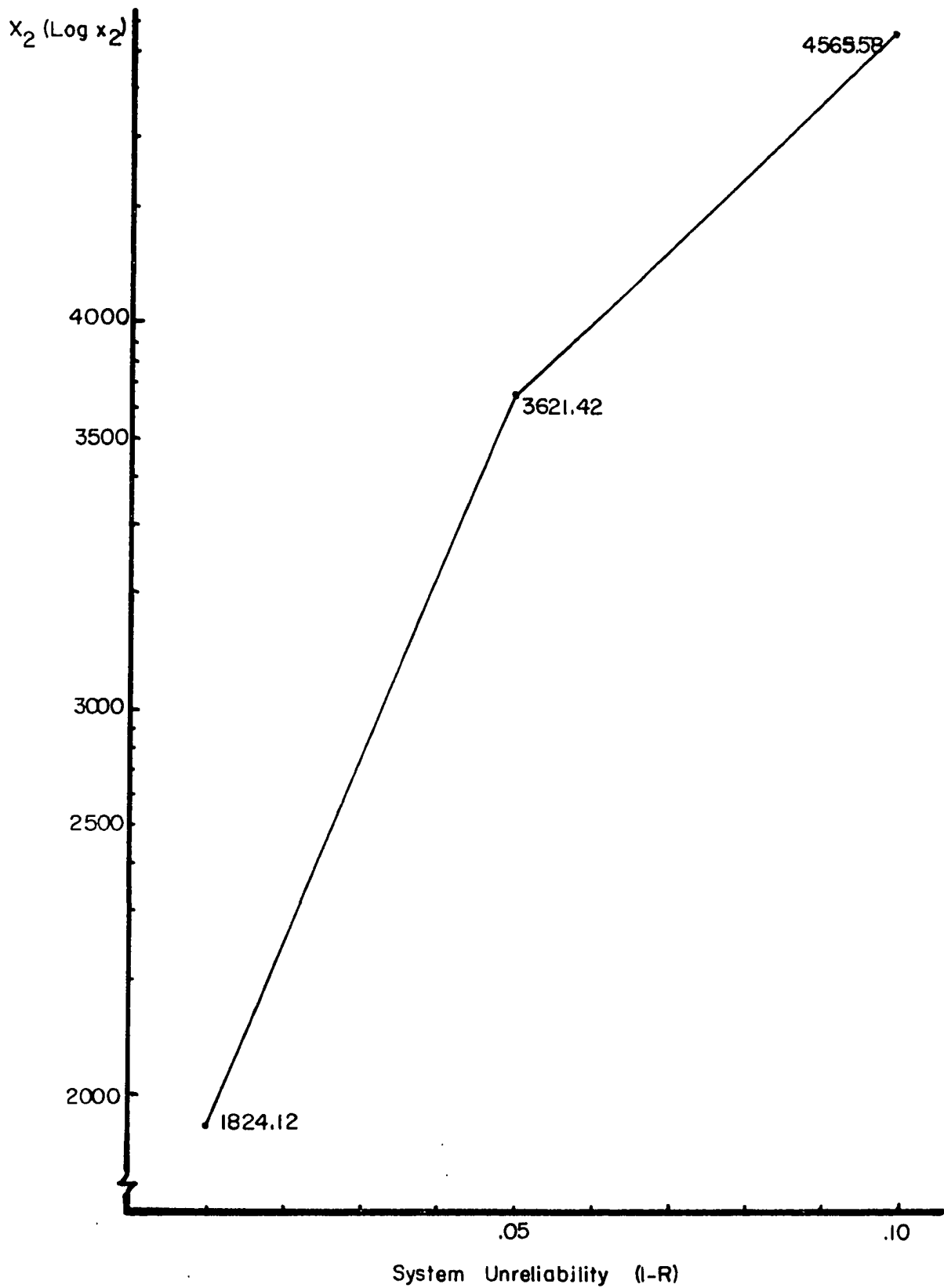


Figure 4.2.3. Curve between  $X_2$  and Systems Unreliability.

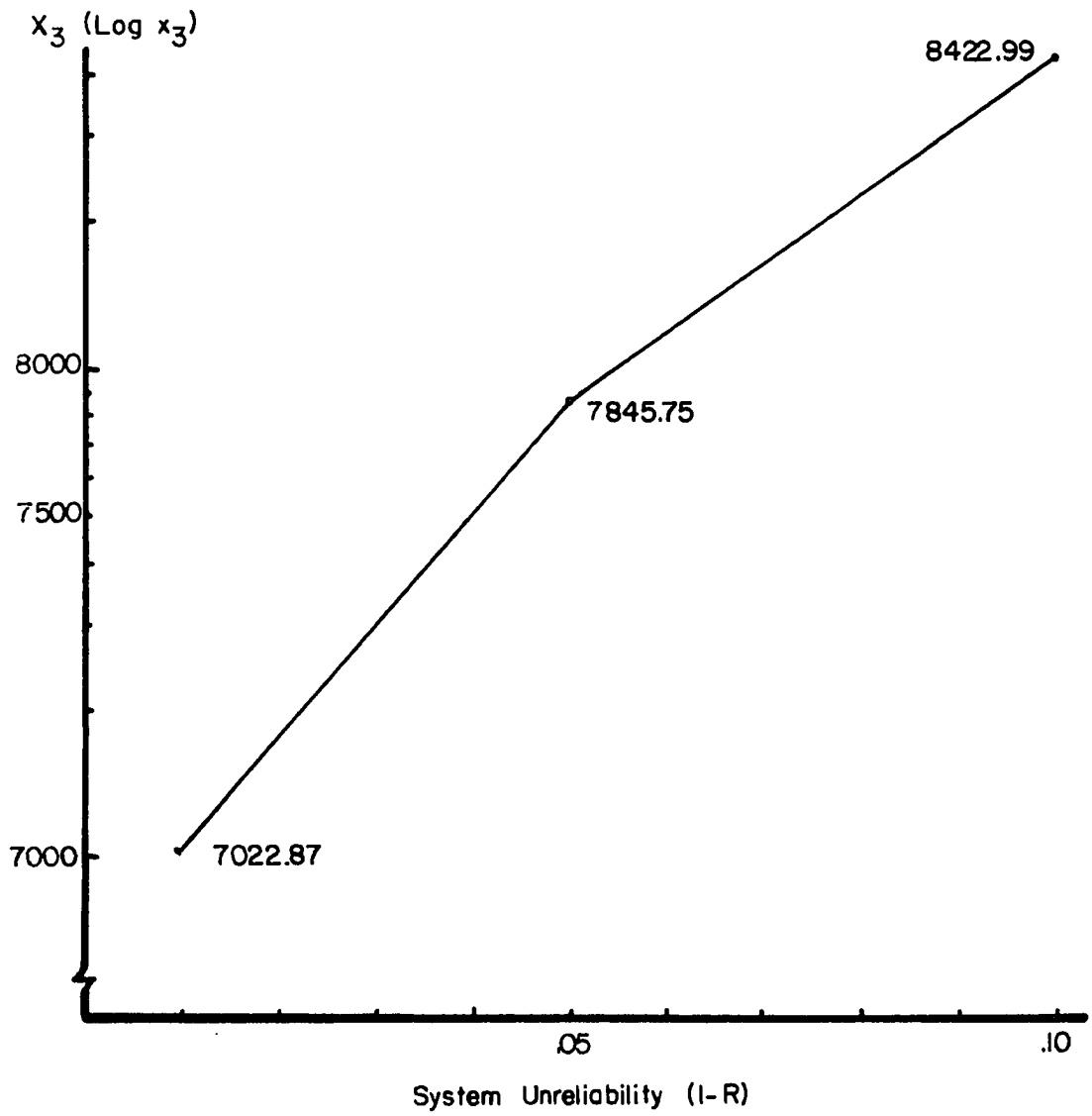


Figure 4.2.4. Curve between  $X_3$  and Systems Unreliability

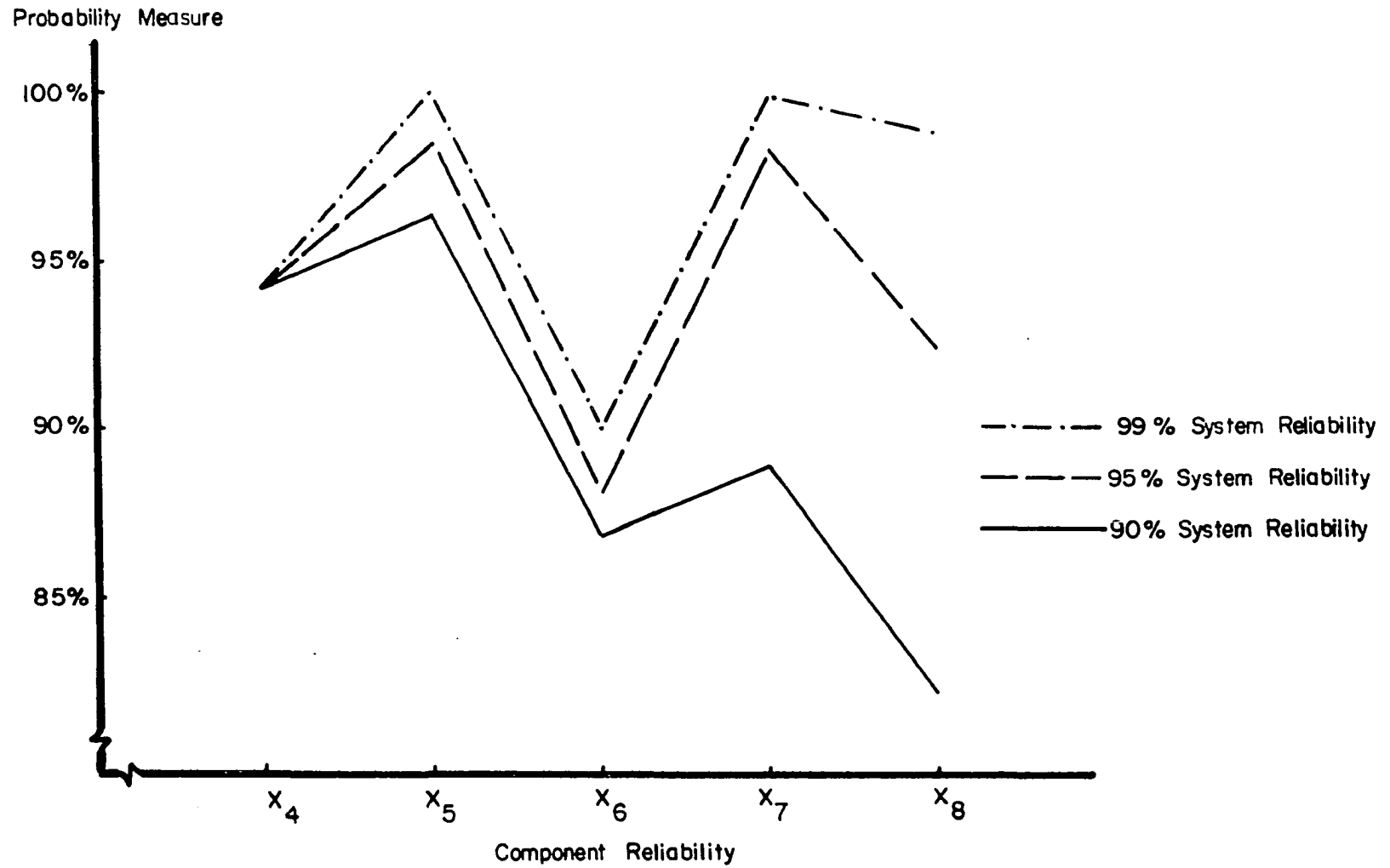


Figure 4.2.5. Curves of Component Reliability due to Changes in System Reliability.



from 4565.58 to 3621.42 due to a decrease of 5% of system unreliability, while for decreasing system unreliability to 1% (i.e. 4% less) we have to decrease  $x_2$  to 1824.12, which is almost half the value  $x_2$  has at 5%.

From Figure 4.2.4 we observe that a decrease of 5% of system unreliability that is from 10% to 5% produces a decrease of 577.60 in  $x_3$  while  $x_3$  varies 822.52 from a decrease from 5% to 1%.

Table 4.2.4. Optimal solutions for optimization models of reliability programming

	System Reliability $\geq (1.29)^5$ (90%)	System Reliability $\geq (1.65)^5$ (95%)	System Reliability $(2.33)^5$ (99%)
$x_1$	6999.9771	6999.9678	6999.9332
$x_2$	4565.5757	3621.4217	1824.1240
$x_3$	8422.9951	7845.3945	7022.8712
$x_4$	1.5714071 (94.18%) <sup>a</sup>	1.5714070 (94.18%)	1.5713972 (94.18%)
$x_5$	1.7935038 (96.33%)	2.1741886 (98.50%)	3.9879089 (100%)
$x_6$	1.1247981 (86.86%)	1.1830666 (88.10%)	1.2825744 (89.97%)
$x_7$	1.2232458 (88.88%)	2.1224378 (98.30%)	3.8341266 (99.99%)
$x_8$	0.92156265 (82.12%)	1.4258726 (92.36%)	2.2287115 (97.71%)

<sup>a</sup>Probability percent found in a normal distribution Table (14, pp. 127-134), rounded to two decimal figures.

Table 4.2.4 (Continued)

	System Reliability $\geq (1.29)^5$ (90%)	System Reliability $\geq (1.65)$ (95%)	System Reliability $(2.33)^5$ (99%)
$z_1^b$	1000.7009	925.843232	796.57584
$z_2^c$	999.42743	923.33920	792.34642

<sup>b</sup>The value of the objective function as specified in [4.2.24].

<sup>c</sup>The value of the objective function as specified in [4.2.17] that is without the reliability function.

From the above results we point out that variable  $x_2$  is more sensitive in responses to system reliability changes while  $x_1$  is less;  $x_3$  has small changes compared to  $x_2$ ; thus we can say that  $x_2$  is the more crucial variable in our problem of reliability programming.

In Figure 4.2.5 we observe the changes in component reliability, in other words the probability assigned by the system itself in order to satisfy the stochastic constraints due to a change in the total system reliability.

Note that:

$x_4$  = the risk prescribed for period 1

$x_5$  = the risk prescribed for period 2

$x_6$  = the risk prescribed for period 3

$x_7$  = the risk level for the capital constraint in period 2


$x_8$  = the risk level for the capital constraint in period 3

For our first probabilistic constraint we have a common value of 94.18% that is  $x_4$  is the same for the three values of system reliability. Greater changes occur with 90% system reliability than with 95% and 99% levels. We observe that in the three cases the changes in the components move in the same direction that is, increase or decrease in every component for difference in system reliability. The largest difference in component reliability for difference in system reliability is  $x_8$  which indicates that our last constrained restriction is more sensitive to changes in the total system reliability.

Table 4.2.5. Lagrange multipliers associated with optimization models of reliability programming

Constraints	System Reliability	System Reliability	System Reliability
	$\geq (1.29)^5$ (90%)	$\geq (1.65)^5$ (95%)	$(2.33)^5$ (99%)
$g_1(x)$	0.026795	0.039712	0.042705
$g_2(x)$	0.038744	0.06146	0.054547
$g_3(x)$	0.031901	0.047656	0.053781
$g_4(x)$	0.039046	0.031859	0.019863
$g_5(x)$	0.051422	0.043254	0.014314
$g_6(x)$	0.055033	0.054674	0.028551
$g_7(x)$	11.773290	4.944558	1.175800
$g_8(x)$	$3.29 \times 10^{-6}$	$5.60 \times 10^{-6}$	$1.50 \times 10^{-5}$
$g_9(x)$	$3.98 \times 10^{-6}$	$9.92 \times 10^{-6}$	0.606001
$g_{10}(x)$	$2.35 \times 10^{-6}$	$4.17 \times 10^{-6}$	$1.19 \times 10^{-5}$
$g_{11}(x)$	$2.52 \times 10^{-6}$	$9.38 \times 10^{-6}$	$3.22 \times 10^{-3}$
$g_{12}(x)$	$2.05 \times 10^{-6}$	$4.99 \times 10^{-6}$	$2.82 \times 10^{-5}$

In Table 4.2.5 we indicate the Lagrange multiplier for the three system reliability problems. The most binding constraint is the measure of system reliability (i.e.,  $g_7(x)$ ).

  $g_7(x)$

#### 4.2.2. Sample distribution approach

We have assumed that  $(p_i - p_{i-1})/p_{i-1}$  is approximately normally distributed with mean  $\mu = .05$  and variance  $\sigma^2 = .0225$ . Note however that  $\mu$  and  $\sigma^2$  are population parameters of the normal parent  $N(\mu, \sigma^2)$  and these are not generally observable, i.e., these are unknown constants which are to be estimated from sample observations, unless of course the random variation in  $(p_i - p_{i-1})/p_{i-1}$  around  $\mu$  are generated by a controlled experiment. The later case may arise for example when in a simulation study random numbers are drawn from a normal table with preassigned (i.e. known) mean  $\mu$  and variance  $\sigma^2$ . However in most economic models and other fields of application the parameters  $\mu$ ,  $\sigma$  are unknown and have to be estimated from sample non-experimental observations. Now usually if the sample observations on each  $(p_i - p_{i-1})/p_{i-1}$  are available and these can be seasonably assumed to be random drawings from a normal parent  $N(\mu, \sigma^2)$ , then the sample mean  $\bar{x}$  provides a good estimate of  $\mu$ ; similarly in this case a good estimate  $\hat{\sigma}^2$  of  $\sigma^2$  may be easily defined. We have to note that if the sample mean  $\bar{x}$  is used as unbiased estimate

( $E\bar{x}=\mu$ ) of the parameter  $\mu$ , we should refer to the distribution of the sample mean rather than the population distribution. But since  $\bar{x}$  is normally distributed with expectation  $\mu$  and variance  $\sigma^2/T$ , our problem [4.2.17] will be:

$$\text{Max } .05x_1 + .05x_2 + .05x_3$$

subject to

$$\begin{aligned} g_1(x) &\equiv 1300 + (.05 - \frac{.15}{\sqrt{T}}\psi)x_1 && \geq 0 \\ g_2(x) &\equiv 1000 + (.05 - \frac{.15}{\sqrt{T}})x_2 && \geq 0 \\ g_3(x) &\equiv 1000 + (.05 - \frac{.15}{\sqrt{T}}\psi)x_3 && \geq 0 \\ g_4(x) &\equiv 7000 - x_1 && \geq 0 \\ g_5(x) &\equiv 5500 + (.05 - \frac{.15}{\sqrt{T}}\psi)x_1 - x_2 && \geq 0 \\ g_6(x) &\equiv \frac{-.15}{\sqrt{T}}\phi\sqrt{x_1^2 + x_2^2} + 9000 + .05x_1 + .05x_2 - x_3 && \geq 0 \end{aligned}$$

In Table 4.2.6 we show different solutions of the above problem for sample size of 1, 4, 9, 16, 25, 36, 49, 64, 81, 100, 121, 144 units. We observe the increase in profit as  $T$  increase, we have that with 4 units we got a profit of 934.32 while for 144 units we got 1091.42 of profit.

From Figure 4.2.6 we can see that the curve of profit due to changes in the sample size increases rapidly in profit at the beginning. Then it has a slow variation that implies

a diminishing return of profit due to an increase in the sample size.

One possible way to find an optimal sample size will be to draw a tangent line to the profit-sample size curve which is parallel to net line

$$z = a + b\sqrt{n}$$

where

$z$  = profit

$\sqrt{n}$  = square root of the sample size

$a$  = intercept

$b$  = slope

That point will give us how much profit we will get with that sample size.

Let us have an example with  $a=0$ ,  $b=10$  so our line is  $z=10\sqrt{n}$ , the optimal point may be  $\sqrt{n}=6$  and  $z=1058.84$ . Many other points could be found if we knew the parameters  $a$ , and  $b$ .

In the case the sample size increases to infinite we observe that the term  $.15\sqrt{T}$  goes to zero and our nonlinear programming becomes the following linear programming problem.

$$\text{Max } .05x_1 + .05x_2 + .05x_3$$

Table 4.2.6. Profit variation due to sample size variation<sup>a</sup>

$\sqrt{T}$	Sample T	z	$x_1$	$x_2$	$x_3$
1	1	756.74	6581.35	3528.65	5024.71
2	4	934.52	6999.78	4626.58	7063.95
3	9	995.55	6999.72	5034.26	7877.03
4	16	1026.65	6999.79	5238.18	8300.29
5	25	1045.99	6999.72	5360.44	8559.76
6	36	1058.84	6999.69	5441.95	8735.16
7	49	1068.08	6999.70	5500.50	8861.65
8	64	1075.07	6999.897	5544.08	8957.39
9	81	1080.50	6999.876	5578.04	9032.07
10	100	1084.86	6999.86	5605.21	9092.07
11	121	1088.43	6999.856	5627.44	9141.32
12	144	1091.42	6999.85	5645.97	9182.47
$\infty$	$\infty$	1124.63	7000.0	5850.0	9462.50

<sup>a</sup>Decimal values are rounded.

subject to

$$7000 - x_1 \geq 0$$

$$5500 + .05x_1 - x_2 \geq 0$$

$$9000 + .05x_1 + .05x_2 - x_3 \geq 0$$

$$x_1, x_2, x_3 \geq 0$$

Solving this problem using MPS (Mathematical Programming System) (69, 70), we get an optimal solution as  $x_1=7000.$ ,  $x_2=5850.$ ,  $x_3=9642.50$  with a value of 1124.63.

In Table 4.2.7 we indicate the Lagrange multipliers associated with the sample size variation problems. The most binding constraints are the last three constraints.

We can develop other models where it could include costs of sampling in the objective function.

Another way we could develop this model further is by considering sample distribution problems indicated in (70).



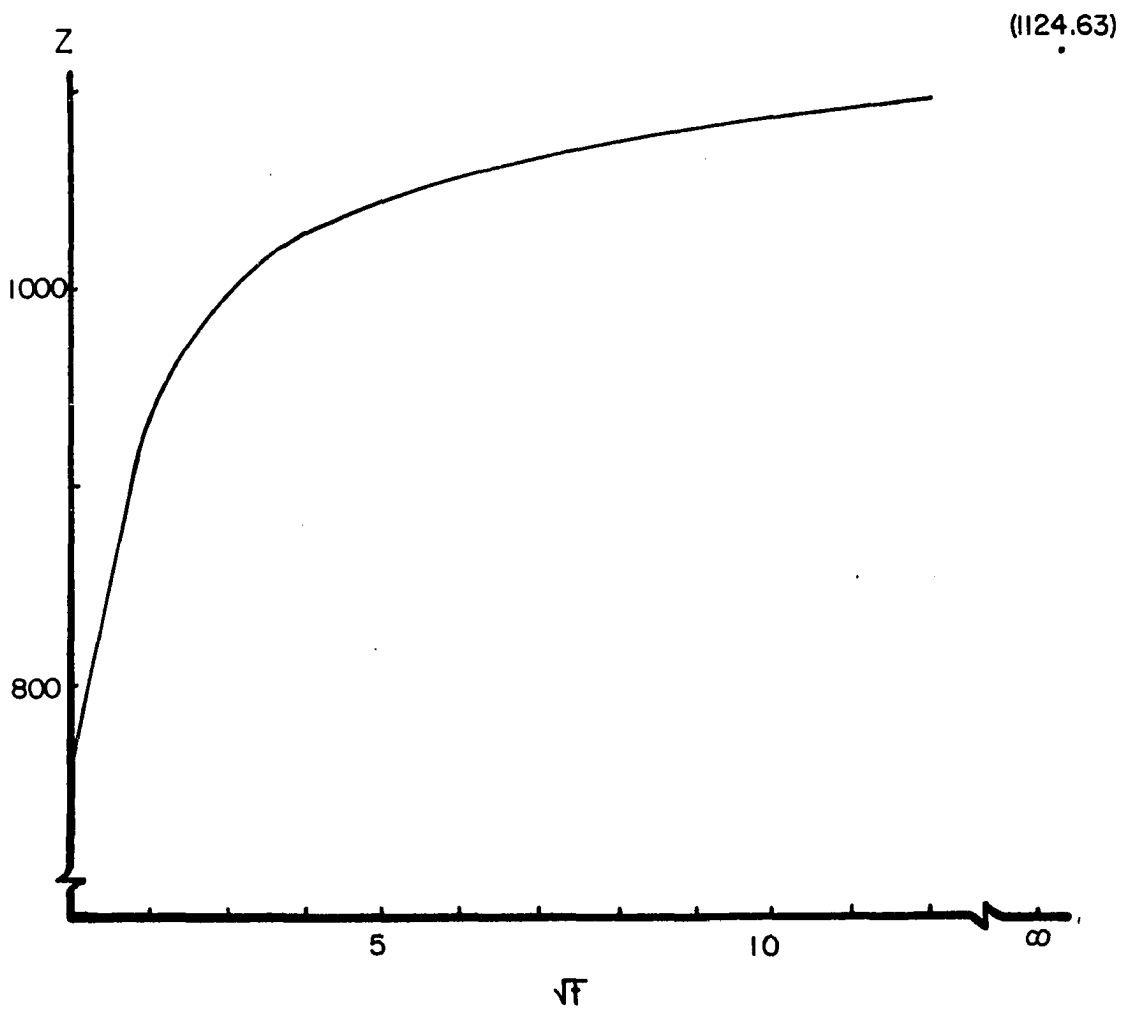


Figure 4.2.6. Variation of Profit due to Change in Sample Size

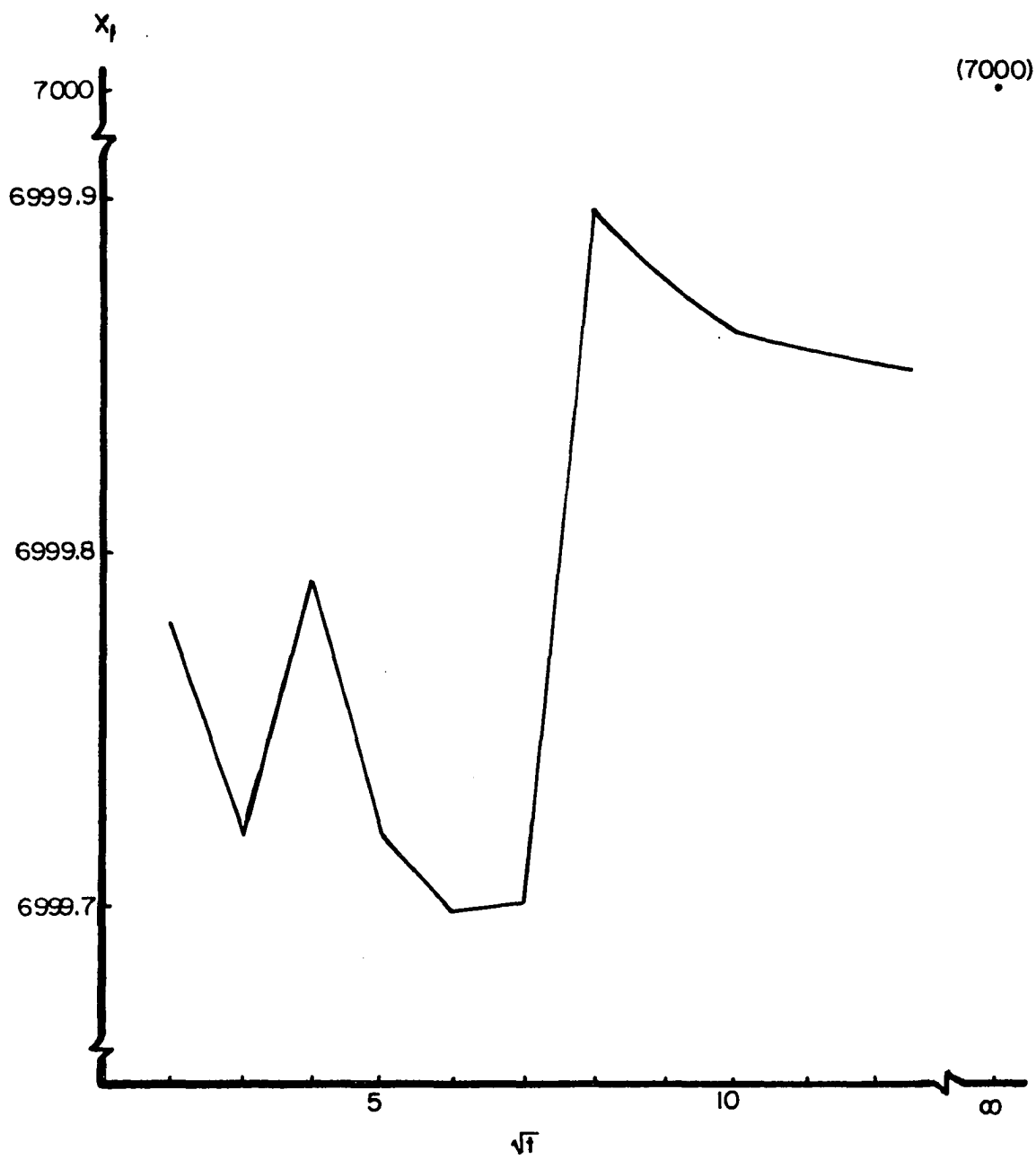


Figure 4.2.7. Variation of  $X_1$  due to Change in Sample Size

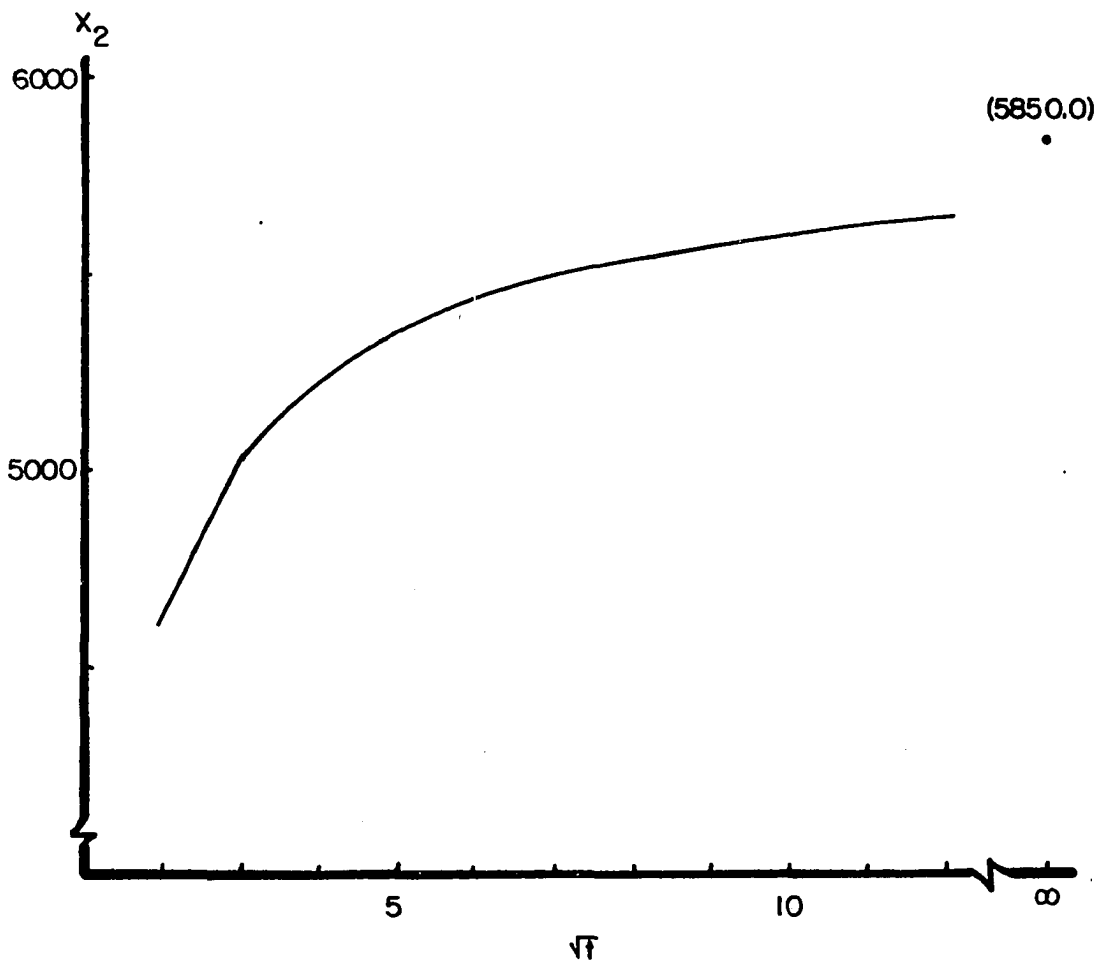


Figure 4.2.8. Variation of  $X_2$  due to Change in Sample Size.

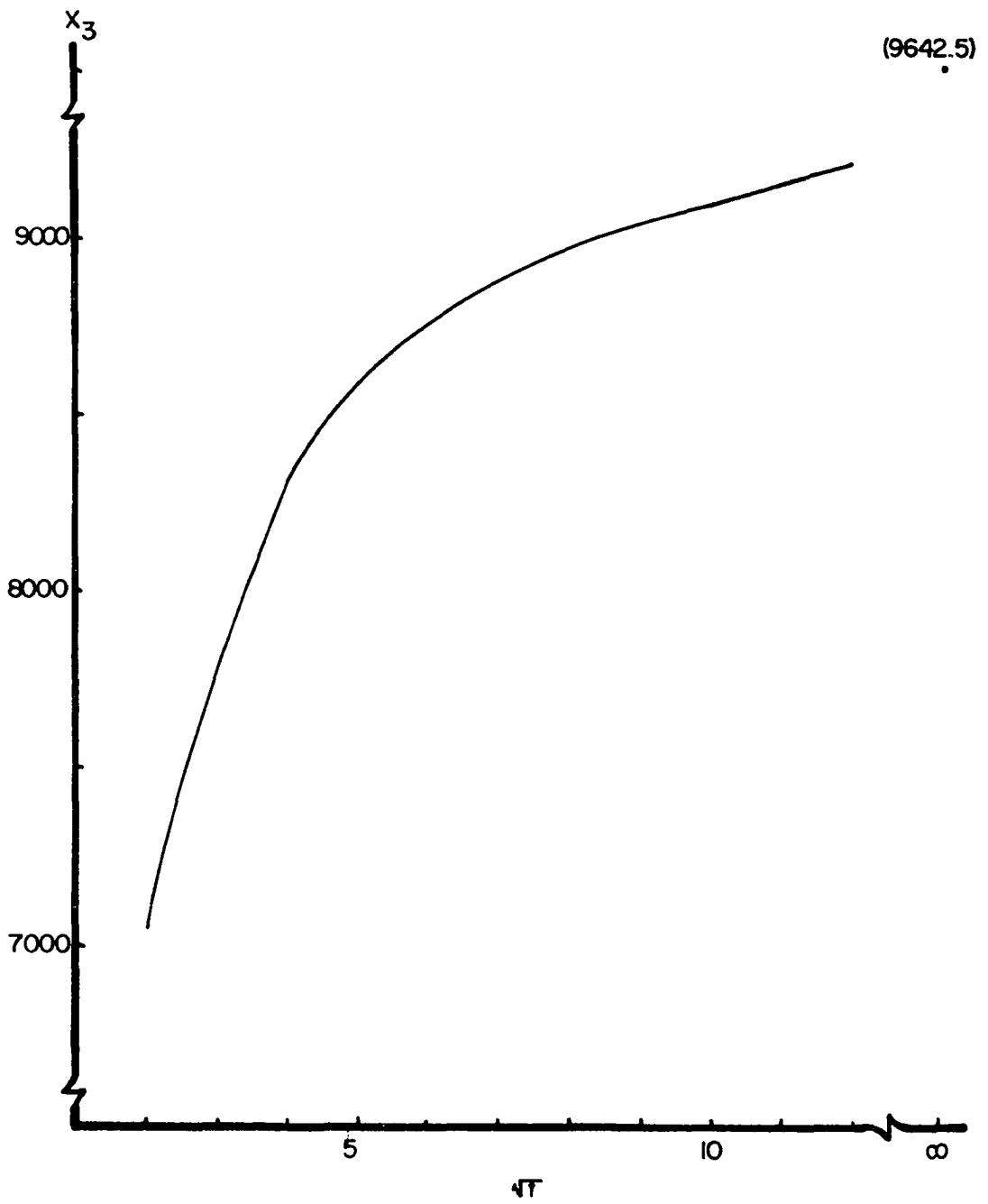


Figure 4.2.9. Variation of  $X_3$  due to Change in Sample Size

Table 4.2.7. Lagrange multipliers associated with the sample size variation problems

Constraint	T=1	T=4	T=9	T=16	T=25	T=36
$g_1(x)$	0.061133	$2.86 \times 10^{-9}$	$2.79 \times 10^{-9}$	$1.31 \times 10^{-9}$	$2.09 \times 10^{-9}$	$2.38 \times 10^{-9}$
$g_2(x)$	$2.21 \times 10^{-8}$	$4.06 \times 10^{-9}$	$4.59 \times 10^{-9}$	$2.20 \times 10^{-9}$	$3.54 \times 10^{-9}$	$4.02 \times 10^{-9}$
$g_3(x)$	$3.49 \times 10^{-5}$	$7.67 \times 10^{-9}$	$5.81 \times 10^{-9}$	$2.38 \times 10^{-9}$	$3.53 \times 10^{-9}$	$3.80 \times 10^{-9}$
$g_4(x)$	$1.16 \times 10^{-8}$	0.035103	0.040950	0.044974	0.046905	0.047968
$g_5(x)$	0.035969	0.049626	0.046335	0.048327	0.048909	0.049490
$g_6(x)$	0.046159	0.051142	0.049572	0.050481	0.050284	0.049591

Table 4.2.7 (Continued)

Constraint	T=49	T=64	T=81	T=100	T=121	T=144	T= $\infty$
$g_1(x)$	$2.33 \times 10^{-9}$	$2.62 \times 10^{-10}$	$3.66 \times 10^{-10}$	$4.33 \times 10^{-10}$	$4.79 \times 10^{-10}$	$5.12 \times 10^{-10}$	-
$g_2(x)$	$3.92 \times 10^{-9}$	$4.39 \times 10^{-10}$	$6.14 \times 10^{-10}$	$7.24 \times 10^{-10}$	$7.99 \times 10^{-10}$	$8.55 \times 10^{-10}$	-
$g_3(x)$	$3.59 \times 10^{-9}$	$3.92 \times 10^{-10}$	$5.37 \times 10^{-10}$	$6.24 \times 10^{-10}$	$6.81 \times 10^{-10}$	$7.20 \times 10^{-10}$	-
$g_4(x)$	0.049226	0.050290	0.050679	0.051076	0.051444	0.051604	0.05512
$g_5(x)$	0.049789	0.049784	0.049806	0.049970	0.050234	0.050328	0.05250
$g_6(x)$	0.050149	0.050454	0.050334	0.050296	0.050299	0.050180	0.05000

## 5. APPLIED GEOMETRIC PROGRAMMING

### 5.1. A Simple Stochastic Production Model: an Illustration

An entrepreneur transforms inputs into outputs, subject to the technical rules specified by his production function.

The entrepreneur's production function gives mathematical expression to the relationship between the quantities of inputs he employs and the quantity of output he produces. A specific production function may be given by a single point, a single continuous or discontinuous function, or a system of equations (63).

We limit here to a production function given by a single continuous function with continuous first- and second-order partial derivatives. The analysis is first developed for the simple case in which three inputs are combined for the production of a single output and then extended to stochastic case.

So we have three inputs called,  $x_1$ , labor;  $x_2$ , raw materials and  $x_3$  capital, the cost of production  $c$  is given by the linear equation

$$c = .14x_1 + .04x_2 + .06x_3$$

the production function is given by:

$$y = 100 x_1^{1.6} x_2^{.5} x_3^{.7}$$

Note that this production function assumes increasing returns to scale, the following

$$y \geq 1000$$

and labor to capital ratio must be

$$\frac{x_1}{x_3} \leq 10; \frac{x_1}{x_3} \geq 5$$

then we will have the following programming problem

$$\text{Min } .14x_1 + .04x_2 + .06x_3$$

subject to

$$100x_1^{1.6}x_2^{.5}x_3^{.7} \geq 1000$$

$$\frac{x_1}{x_3} \leq 10$$

$$\frac{x_1}{x_3} \geq 5$$

The geometric programming formulation will be

$$\text{Min } .14x_1 + .04x_2 + .06x_3$$

subject to

$$10x_1^{-1.6}x_2^{-.5}x_3^{-.7} \leq 1$$

$$.1x_1x_3^{-1} \leq 1$$

$$5x_1^{-1}x_3 \leq 1$$

The degree of difficulty is two, because we have six terms and three variables, the dual will be

$$\text{Max } \left(\frac{.14}{\delta_1}\right)^{\delta_1} \left(\frac{.04}{\delta_2}\right)^{\delta_2} \left(\frac{.06}{\delta_3}\right)^{\delta_3} \left(\frac{10}{\delta_4}\right)^{\delta_4} \left(\frac{.1}{\delta_5}\right)^{\delta_5} \left(\frac{5}{\delta_6}\right)^{\delta_6}$$

subject to

$$\delta_1 + \delta_2 + \delta_3 = 1$$

$$\delta_1 - 1.6\delta_4 + \delta_5 - \delta_6 = 0$$

$$\delta_2 - .5\delta_4 = 0$$

$$\delta_3 - \delta_4 + \delta_5 + \delta_6 = 0$$

$$\delta_1, \delta_2, \delta_3 \geq 0$$

Solving the problem we have that:

$$g_0(x) = .6516, \quad x_1 = 3.5213, \quad x_2 = 2.9089, \quad x_3 = 0.7043$$

and the dual variables are:

$$v(\delta) = .6516, \quad \delta_1 = 0.75658, \quad \delta_2 = 0.17857, \quad \delta_3 = 0.06485$$

$$\delta_4 = 0.35714, \quad \delta_5 = 5.347 \times 10^{-8}, \quad \delta_6 = 0.18515$$

as we have two degrees of difficulty we do not have any economical interpretation of the dual variables.

As an easy way to deal with a stochastic case we can assume that production has to match sales, which is a random variable with normal distribution with mean equal to 1000 units and variance equal to 100, so our model now is

$$\text{Min } .14x_1 + .04x_2 + .06x_3 \quad [5.1.1]$$



subject to

$$\text{Prob}(y \geq y^*) \geq u \quad [5.1.2]$$

$$y = 100x_1^{1.6}x_2^{.5}x_3^{.7}$$

$$\frac{x_1}{x_3} \leq 10$$

$$\frac{x_1}{x_3} \geq 5$$

where  $y^*$  is a random variable with a normal distribution with  $\bar{y}=1000$  and  $\sigma^2=100$ . The constraint [5.1.2] will be

$$\text{Prob}(y^* \leq 100x_1^{1.6}x_2^{.5}x_3^{.7}) \geq u$$

$$\text{Prob}\left(\frac{y^* - \bar{y}}{\sigma} \leq \frac{100x_1^{1.6}x_2^{.5}x_3^{.7} - \bar{y}}{\sigma}\right) \geq u$$

now if we define

$$I(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-y^2/2} dy$$

we have

$$I\left(\frac{100x_1^{1.6}x_2^{.5}x_3^{.7} - \bar{y}}{\sigma}\right) \geq u$$

$$\frac{100x_1^{1.6}x_2^{.5}x_3^{.7} - \bar{y}}{\sigma} \geq I^{-1}(u)$$

Let us make  $I^{-1}(u) = x_4$  then

$$100x_1^{1.6}x_2^{.5}x_3^{.7} \geq \bar{y} + \sigma I^{-1}(u)$$

$$100x_1^{1.6}x_2^{.5}x_3^{.7} \geq 1000 + 10x_4$$

Then we will have the following geometric problem

$$\begin{aligned} &\text{Min } .14x_1 + .04x_2 + .06x_3 + x_4 \\ &\text{subject to} \\ &100x_4^{-1} - 10x_1^{1.6}x_2^{.5}x_3^{.7} \leq 1 \\ &.1x_1x_3 \leq 1 \\ &5x_1^{-1}x_3 \leq 1 \\ &1.65x_4^{-1} \leq 1 \end{aligned}$$

we note that we have added a penalty function  $x_4$  to the objective function and added a lower bound to  $x_4$  (i.e.  $x_4 \geq a^*$ ) in the present case we assume that the probability level  $u$  must be greater than 90%, 97%, 99%. We note that the first constraint is not a posynomial (positive polynomial) so we are dealing with the case of a generalized polynomial programming (138, 16). The problem has four degrees of difficulty and the results are given in Table 5.1.1 and the dual results are given in Table 5.1.2.

Table 5.1.1. Primal results

Variable	$a^*=1.65$ 90%	$a^*=1.88$ 97%	$a^*=2.33$ 99%
$x_1$	2.9272	2.7915	2.5814
$x_2$	2.4181	2.3061	2.1324
$x_3$	0.5854	0.5583	0.5163
$x_4$	1.65	1.88	2.33
$z$	.5417	.5166	.4377

Table 5.1.2. Dual results

Variable	a*=1.65 90%	a*=1.88 97%	a*=2.33 99%
$\delta_1$	0.1869	0.1631	0.1287
$\delta_2$	0.0441	0.0385	0.0304
$\delta_3$	0.0160	0.0139	0.0103
$\delta_4$	0.7529	0.7845	0.8299
$\delta_5$	0.0897	0.0785	0.0622
$\delta_6$	0.0883	0.0769	0.0608
$\delta_7$	$4.24 \times 10^{-8}$	$4.50 \times 10^{-8}$	$4.43 \times 10^{-8}$
$\delta_8$	0.0458	0.0399	0.0315
$\delta_9$	0.6631	0.7060	0.7677

## 5.2. An Aggregative Model of Economic Growth: a Second Illustration

Hirofumi Uzawa (134), discussed the problem of optimum fiscal policy in terms of the technique of optimum economic growth. He pointed out that his model is a simple extension of the aggregative growth model of the type introduced by Solow (124), Swan (127) and Tobin (133). We use Uzawa's model, in order to show an application of geometric programming, with some simplifying assumptions.

The Uzawa model consists of private and public sectors, both employing labor and private capital to produce goods and services. Private goods may be either consumed or

accumulated as capital, while public goods are all consumed. The public sector raises revenues by levying income taxes. The private sector decides how much is to be consumed and invested and how to allocate portfolio balances between real capital and money. These decisions are based upon certain behavioristic assumptions and are made in a perfectly competitive institutional setting. Uzawa had shown that by a proper choice of dynamic fiscal policy, which consists of income tax rates and growth rates of money supply through time, it is possible to achieve an optimal growth path corresponding to certain forms of social utility function properly discounted.

We consider an economic system composed of public and private sectors. The private sector comprises business firms and households; business firms employ labor and either own or rented capital, while households receive wages for the labor they provide and interest and dividends for the capital they rent to business firms. The output produced in the private sector is assumed to be composed of homogeneous quantities so that any portion of it may be either instantaneously consumed or accumulated as part of the capital stock. The public sector will provide the private sector with different goods and services than those it produces. The goods and services produced in the public sector are assumed to be measurable and distributed uniformly to the private sector

without cost. The public sector raises revenues through income taxes and increases in the money supply to pay wages and rentals for the private means of production it employs. It is required to employ labor and capital in such a way that total expenditure is minimized for any level of public goods produced. The public sector has two means of raising revenues, they are taxation and printing money, but is assumed to be able to control only the rate of income tax and the rate of increase in money supply. Capital accumulation takes place only in the private sector and public goods are not accumulated. Uzawa has analyzed the problem of optimum investment in public capital in which all public goods are regarded as social capital to increase productivity of labor and as private capital in the private sector.

The aggregation output at moment  $t$ ,  $Y_c(t)$  in the private sector is assumed to depend only on the amounts of capital  $K_c(t)$  and labor,  $L_c(t)$ , employed, so we have a private sector's productive function  $F_c$  then

$$Y_c(t) = F_c(K_c(t), L_c(t)) \quad [5.2.1]$$

The production processes are assumed to be subject to constant return to scale and to a positive diminishing marginal rate of substitution between capital and labor. Perfect competition prevails in the private sector, so that the real wage,  $w(t)$ , and the real rental rate,  $r(t)$ , are equated to

the marginal products of labor and capital, respectively

$$w(t) = \frac{\partial F_C}{\partial L_C} \quad r(t) = \frac{\partial F_C}{\partial K_C}$$

The aggregative output in the public sector at time  $t$ , is  $Y_V(t)$  and it depends on capital  $K_V(t)$  and labor  $L_V(t)$  which it employs in such a combination that the total cost in terms of market prices is always minimized. So we have

$$Y_V(t) = F_V(K_V(t), L_V(t)) \quad [5.2.2]$$

the public sector's production function,  $F_V$ , is assumed to be homogeneous of order one and strictly quasi-concave, with positive marginal products everywhere.

We know by the marginal theory that, the cost in the public sector is minimized when the marginal rate of substitution between labor and capital is equated to the wage-rentals ratio  $w(t)/r(t)$ , at time  $t$ .

$$\frac{\partial F_V / \partial L_V}{\partial F_V / \partial K_V} = \frac{w(t)}{r(t)}$$

the real gross national income  $Y(t)$ , is given by

$$Y(t) = r(t)K(t) + w(t)L(t) \quad [5.2.3]$$

Since the quantities of capital and labor available are  $K(t)$  and  $L(t)$ , we have

$$K(t) = K_C(t) + K_V(t) \quad [5.2.4]$$

$$L(t) = L_C(t) + L_V(t) \quad [5.2.5]$$

The output of private goods,  $Y_c(t)$  is divided between consumption,  $C(t)$  and investment,  $Z(t)$  so:

$$Y_c(t) = C(t) + Z(t) \quad [5.2.6]$$

The accumulation of capital is described by

$$\dot{K}(t) = Z(t) - \mu K(t) \quad [5.2.7]$$

where  $\mu$  is the rate of depreciation, while the growth rate of labor,  $n$ , is assumed to be exogeneously given:

$$\dot{L}(t) = nL(t) \quad [5.2.8]$$

The desired level of investment, on the other hand, is determined by the Keynesian principle of marginal efficiency of investment, as mathematically formulated by Uzawa in (135). Business firms in the private sector try to increase the level of investment to that at which the supply price of capital is equated with the demand price (defined as the discounted sum of the expected return). In general, the desired level of investment,  $Z(t)$  is determined by the current rate of return,  $r(t)$ , the money price,  $p(t)$ , the rate of interest  $p(t)$ , and the stock of capital,  $K(t)$ .

As Uzawa pointed out public goods are regarded as consumption goods, while private goods can either be consumed instantaneously or accumulated as capital. The utility function of representative members of the society depends upon

the amount of private goods to be consumed and upon the average quantity of public goods available at each moment, for the sake of simplicity. Public goods are assumed to be distributed equally among the members of the society. If we defined  $u(c,x)$  as a utility function where  $c$  and  $x$  stand respectively for the quantities of per capita consumption of private and public goods. He assumed that the social welfare function is represented as the discounted sum of instantaneous utilities through time; then we have

$$\int_0^{\infty} u(c,x) e^{-\delta t} dt \quad [5.2.9]$$

where  $\delta$  is the rate by which future utilities are compared with the present utilities with a proper modification when the population is not stationary.

Uzawa reformulates the problem of optimum fiscal policy, as this, he supposes that the public sector can determine or influence not only the fiscal policy but also the allocations of capital and labor between sectors and the division of private goods between consumption and investment. The public sector then seeks that feasible time-path of factor and output allocations at which the utility functional (5.2.9) is maximized. This time path, if it exists, will be called optimum path of economic growth.

So we have the following programming problem



$$\text{Max} \int_0^{\infty} u\left[\frac{C(t)}{L(t)}, \frac{X(t)}{L(t)}\right] e^{-\delta t} dt \quad [5.2.10]$$

subject to

$$C(t) + Z(t) \leq F_C(K_C(t), L_C(t))$$

$$X(t) \leq F_V(K_V(t), L_V(t))$$

$$K_C(t) + K_V(t) \leq K(t)$$

$$L_C(t) + L_V(t) \leq L(t)$$

$$\dot{K}(t) = (t) - \mu K(t)$$

$$\dot{L}(t) = nL(t)$$

when all variables are nonnegative and the initial capital  $K(0)$  and labor  $L(0)$  are given.

If we omit the time suffix for the sake of simplicity and we use small letters to indicate the quantities per capita, the programming problem of optimum economic growth is reduced to the following

$$\text{Max} \int_0^{\infty} u(c, x) e^{-\delta t} dt \quad [5.2.11]$$

subject to

$$c+z \leq f_C(k_C)l_C \quad [5.2.12]$$

$$x \leq f_V(k_V)l_V \quad [5.2.13]$$

$$k_C l_C + k_V l_V \leq k \quad [5.2.14]$$

$$l_C + l_V \leq 1 \quad [5.2.15]$$

$$\dot{k} \geq z - (n+\mu)k \quad [5.2.16]$$

We will try to solve the above programming problem, with some simplifying assumptions, first we assume a static

problem and the change of capital stock is constant and known:

$$\frac{\dot{k}}{k} = 5\% \text{ (say)} \quad [5.2.17]$$

From [5.2.16] and [5.2.17] we get that

$$\begin{aligned} z &\geq .05k + (n+\mu)k \\ z &\geq (n+\mu+.05)k \end{aligned} \quad [5.2.18]$$

if we have that the rate of depreciation  $\mu$  is equal to 6% and the growth rate  $n$  is equal to 4% we have that [5.2.18] is:

$$z \geq 1.5k$$

if we assume that the capital stock  $k$  is given and equal to 10 we have

$$z \geq 15$$

In order to evaluate numerically we consider the following specifications

$$\mu(c, x) = c^{.6} x^{.4}$$

$$f_c(k_c) = k_c^{.8}$$

$$f_v(k_v) = k_v^{.9}$$

now if we replace these expressions in our programming problem [5.2.11] we have

$$\begin{aligned} &\text{Max } c^{.6} x^{.4} \\ &\text{subject to} \end{aligned}$$

$$c+z \leq k_c \cdot 8 l_c$$

$$x \leq k_v \cdot 9 l_v$$

$$k_c l_c + k_v l_v \leq 10$$

$$l_c + l_v \leq 1$$

$$z \geq 15$$

The utility function  $u(c,x)$  is continuously twice differentiable and has positive marginal utilities  $\frac{\partial u}{\partial c}$  and  $\frac{\partial u}{\partial x}$  for all positive  $c$  and  $x$ ;  $u(c,x)$  is concave in the sense that the Hessian matrix

$$\underline{H} = \begin{bmatrix} \frac{\partial^2 u}{\partial c^2} & \frac{\partial^2 u}{\partial c \partial x} \\ \frac{\partial^2 u}{\partial c \partial x} & \frac{\partial^2 u}{\partial x^2} \end{bmatrix}$$

is negative semi-definite for all values of  $c$  and  $x$ .

Private goods are not inferior; the income-consumption curve has a positive slope; these conditions are summarized as:

$$\frac{\partial u}{\partial c} > 0, \quad \frac{\partial u}{\partial x} > 0$$

$$\frac{\partial^2 u}{\partial c^2} < 0, \quad \frac{\partial^2 u}{\partial x^2} < 0$$

$$|H| = \frac{\partial^2 u}{\partial c^2} \frac{\partial^2 u}{\partial x^2} - \left( \frac{\partial^2 u}{\partial c \partial x} \right)^2 \geq 0$$

$$\frac{\frac{\partial^2 u}{\partial x^2}}{\frac{\partial u}{\partial x}} - \frac{\frac{\partial^2 u}{\partial c \partial x}}{\frac{\partial u}{\partial x}} < 0, \quad \frac{\frac{\partial^2 u}{\partial c^2}}{\frac{\partial u}{\partial c}} - \frac{\frac{\partial^2 u}{\partial x \partial c}}{\frac{\partial u}{\partial x}} < 0$$

To cast our programming problem into a typical geometric programming formulation let us make the following change of variables.

$$c = x_1$$

$$x = x_2$$

$$z = x_3$$

$$k_c = x_4$$

$$k_v = x_5$$

$$l_v = x_6$$

$$l_c = x_7$$

In order to maximize the objective function we minimize the inverse of the original objective function. I report I failed to minimize the objective function changing only the sign of it, which produced overflows and underflows in the computer output.

Now our programming problem will be

$$\text{Min } x_1^{-.6} x_2^{-.4}$$

subject to

$$x_1 + x_3 \leq x_4^{.8} x_7$$

$$x_2 \leq x_5^{.9} x_7$$

$$x_4 x_7 + x_5 x_6 \leq 10$$

$$x_6 + x_7 \leq 1$$

$$x_3 \geq 1.5$$

we had added two restrictions in order to avoid unbounded objective function values, e.g.,

$$x_1^{.6} x_2^{.4} \leq 10$$

$$x_1^{.6} x_2^{.4} \geq .1$$

Finally our programming problem in the typical geometric programming formulation is:

$$\text{Min } x_1^{-.6} x_2^{-.4}$$

subject to

$$x_1 x_4^{-.8} x_7^{-1.} + x_3 x_4^{-.8} x_7^{-1.} \leq 1$$

$$x_2 x_5^{-.9} x_6^{-1} \leq 1$$

$$0.1 x_4 x_7 + 0.1 x_5 x_6 \leq 1$$

$$x_6 + x_7 \leq 1$$

$$\begin{aligned}
 1.5x_3^{-1} &\leq 1 \\
 0.1x_1^{.6}x_2^{.4} &\leq 1 \\
 0.1x_1^{-.6}x_2^{-.4} &\leq 1
 \end{aligned}$$

We have a geometric programming problem with three degrees of difficulty that is we have eleven terms minus seven variables minus one. We observe that all the expressions are posynomials.

The dual program associated with this problem consists of maximizing the dual function

$$\begin{aligned}
 v(\underline{\delta}) = & \left(\frac{1}{\delta_1}\right)^{\delta_1} \left(\frac{1}{\delta_2}\right)^{\delta_2} \left(\frac{1}{\delta_3}\right)^{\delta_3} \left(\frac{1}{\delta_4}\right)^{\delta_4} \left(\frac{0.1}{\delta_5}\right)^{\delta_5} \left(\frac{0.1}{\delta_6}\right)^{\delta_6} \left(\frac{1}{\delta_7}\right)^{\delta_7} \times \\
 & \left(\frac{1}{\delta_8}\right)^{\delta_8} \left(\frac{1}{\delta_9}\right)^{\delta_9} \left(\frac{0.1}{\delta_{10}}\right)^{\delta_{10}} \left(\frac{0.1}{\delta_{11}}\right)^{\delta_{11}} (\delta_2 + \delta_3)^{\delta_2 + \delta_3} (\delta_4)^{\delta_4} \times \\
 & (\delta_5 + \delta_6)^{\delta_5 + \delta_6} (\delta_7 + \delta_8)^{\delta_7 + \delta_8} (\delta_8)^{\delta_8} (\delta_9)^{\delta_9} (\delta_{10})^{\delta_{10}} (\delta_{11})^{\delta_{11}}
 \end{aligned}$$

Simplifying we have

$$\begin{aligned}
 \text{Max } v(\underline{\delta}) = & \left(\frac{1}{\delta_1}\right)^{\delta_1} \left(\frac{1}{\delta_2}\right)^{\delta_2} \left(\frac{1}{\delta_3}\right)^{\delta_3} \left(\frac{0.1}{\delta_5}\right)^{\delta_5} \left(\frac{0.1}{\delta_6}\right)^{\delta_6} \left(\frac{1}{\delta_7}\right)^{\delta_7} (0.1)^{\delta_{10}} \times \\
 & (0.1)^{\delta_8} (\delta_2 + \delta_3)^{\delta_2 + \delta_3} (\delta_5 + \delta_6)^{\delta_5 + \delta_6} (\delta_7 + \delta_8)^{\delta_7 + \delta_8} \dots
 \end{aligned}$$

subject to nonnegative dual variables

$$\begin{aligned}
 \delta_1 \geq 0, \delta_2 \geq 0, \delta_3 \geq 0, \delta_4 \geq 0, \delta_5 \geq 0, \delta_6 \geq 0, \delta_7 \geq 0, \delta_8 \geq 0, \delta_9 \geq 0, \\
 \delta_{10} \geq 0, \delta_{11} \geq 0
 \end{aligned}$$

and the normality and orthogonality conditions give the linear system

$$\begin{array}{rcl}
 \delta_1 & & = 1 \\
 -.6\delta_1 + \delta_2 & & +.6\delta_{10} - .6\delta_{11} = 0 \\
 -.4\delta_1 & +\delta_4 & +.4\delta_{10} - .4\delta_{11} = 0 \\
 & \delta_3 & -\delta_7 = 0 \\
 & -.8\delta_2 - .8\delta_3 & +\delta_5 = 0 \\
 & & -.9\delta_4 & +\delta_6 = 0 \\
 & & -\delta_4 & +\delta_6 & +\delta_8 = 0 \\
 & -\delta_2 & -\delta_3 & +\delta_5 & +\delta_9 = 0
 \end{array}$$

The solution of this problem is shown in Appendix C. The primal results are given in Table 5.2.1 and the dual results in Table 5.2.2.

Table 5.2.1. Primal results

Variable	value	
$x_1$	2.898	$c$
$x_2$	2.472	$x$
$x_3$	1.5	$z$
$x_4$	8.163	$k_c$
$x_5$	18.366	$k_v$
$x_6$	0.18008501	$l_v$
$x_7$	0.81991499	$l_c$
$g_0(\underline{x})$	0.3677	$g_0(\underline{x})$
$u(c, \underline{x})$	2.712	$u(c, \underline{x})$

Table 5.2.2 Dual results

Variable	Value
$\delta_1$	1.0
$\delta_2$	0.6
$\delta_3$	0.3106
$\delta_4$	0.4
$\delta_5$	0.7285
$\delta_6$	0.36
$\delta_7$	0.3105
$\delta_8$	0.4
$\delta_9$	0.18211
$\delta_{10}$	$2.3195 \times 10^{-9}$
$\delta_{11}$	$3.3127 \times 10^{-8}$
$v(\underline{\delta})$	0.3677

We have solved a programming problem where the exponents of the objective function add to one (i.e.  $\alpha + \beta = 1$ ) if we increase this sum such that  $\alpha + \beta > 1$  we might have a utility function

$$u(c, x) = c^{.8} x^{.4}$$

we also have the upper and lower bound for our objective function as

$$c^{.8} x^{.4} \leq 10$$

$$c^{.8} x^{.4} \geq .1$$



in Table 5.2.3 we report the results and the dual variables in Table 5.2.5.

Table 5.2.3. Primal result, case II

Variable	Value	
$x_1$	3.2154	$c$
$x_2$	2.06484	$x$
$x_3$	1.5	$z$
$x_4$	8.4998	$k_c$
$x_5$	19.034	$k_v$
$x_6$	0.1456	$l_v$
$x_7$	0.8543	$l_c$
$g_0(\underline{x})$	0.2939	$g_0(\underline{x})$
$u(c, x)$	3.41	$u(c, x)$

Another interesting case (i.e., case III) we have considered, occurs when the change of capital stock  $\dot{k}/k=14\%$  and therefore the investment per capita constraint [5.2.18] will be

$$z \geq (.14 + .04 + .06) \times 10$$

$$z \geq 2.4$$

The results are given in Table 5.2.4, note that we have a decrease in consumption in order to accomplish the investment restrictions, the dual results are given in Table 5.2.5.

Table 5.2.4. Primal results, case III

Variable	Value	
$x_1$	2.3535	$c$
$x_2$	2.0160	$x$
$x_3$	2.4	$z$
$x_4$	8.49	$k_c$
$x_5$	19.1152	$k_v$
$x_6$	0.141659	$l_v$
$x_7$	0.858341	$l_c$
$g_0(\underline{x})$	0.4520	$g_0(x)$
$u(c,x)$	2.24	$u(c,x)$

We summarize one result by saying that consumption of private goods ( $c$ ) in the three cases is higher than that of public goods as is the fraction of labor allocated to produce private goods ( $l_c$ ).

Table 5.2.5. Dual results

Variable	case II	case III
	$c^{.8}x^{.4}$	$c^{.6}x^{.4}$ and $k/k=14\%$
$\delta_1$	1.	1.
$\delta_2$	0.8	0.6
$\delta_3$	0.3732	0.6118
$\delta_4$	0.4	0.4
$\delta_5$	0.9386	.9695
$\delta_6$	0.36	.36
$\delta_7$	0.3732	.6118
$\delta_8$	0.04	0.04
$\delta_9$	0.2346	0.2424
$\delta_{10}$	$9.31 \times 10^{-10}$	$1.29 \times 10^{-9}$
$\delta_{11}$	$3.17 \times 10^{-8}$	$1.15 \times 10^{-8}$
$\sigma(\underline{\delta})$	0.2939	0.4520

## 6. SUMMARY AND GENERALIZATIONS

Methods of risk programming essentially convert a probabilistic linear programming model into a nonlinear deterministic form, since most operational decision rules have to be specified in non-random terms. Nevertheless we have already started with a quadratic programming model in section 4.1 and due to the simplifying assumption of an exponential distribution about sales we stayed with a quadratic problem. We have solved a large quadratic programming problem instead of using some simplifying technique as Holt, Modigliani, Muth and Simon and others originally used (67, 68, 66, 34). Our limitation in the production planning model was to deal with coded data, practical research will be applied to Peruvian firms and the results will be reported elsewhere.

In the multi-period investment under uncertainty, we have solved in the nonlinear fashion because we were more lucky than Näslund, that is we have the SUMT algorithm which also allowed us to solve the nonlinear reliability models. We might have a sensitivity analysis of the nonlinear programming model but that computer program was not available at the time we were beginning to program it. The sample distribution approach gives us some insight about how our optimal solution changes due to an increase in sample size.

We have intended to show how to solve nonlinear programming problems using geometric and generalized polynomial programming in order to indicate that we are able to deal with more complicated models of risk programming that will be produced by assuming different distribution functions.

The maximum likelihood principle (2) gives us an open window for further research in risk programming, for example consider the CCP model

$$\text{Max } c'x$$

$$\text{Prob } [Ax \leq b] \geq u$$

$$x \geq 0; \quad 0 < u < 1$$

If  $b_i$  is assumed a random variable with a normally independent distribution

$$\text{Prob} \left( \frac{b_i - \bar{b}_i}{\sigma_{b_i}} \geq \frac{a_i'x - \bar{b}_i}{\sigma_{b_i}} \right) \geq u_i$$

$$1 - F \left( \frac{a_i'x - \bar{b}_i}{\sigma_{b_i}} \right) \geq u_i$$

The cumulative density function  $F \left( \frac{a_i'x - \bar{b}_i}{\sigma_{b_i}} \right)$  can be expanded by the following approximation (65):

$$F \left( \frac{a_i'x - \bar{b}_i}{\sigma_{b_i}} \right) \approx \frac{1}{2} + \frac{1}{\sqrt{2\pi}} \left( \frac{a_i'x - \bar{b}_i}{\sigma_{b_i}} \right) - \frac{1}{6\sqrt{2\pi}} \left( \frac{a_i'x - \bar{b}_i}{\sigma_{b_i}} \right)^3$$

Let us define  $\xi_i = \frac{a_i'x - \bar{b}_i}{\sigma_{b_i}}$

we have a transformed deterministic problem such as

$$\text{Max } c'x + \sum \ln [1 - F(\xi_i)]$$

subject to

$$x \geq 0$$

or

$$\text{Max } c'x + \sum_{i=1}^m \ln \left( \frac{1}{2} - \frac{1}{\sqrt{2\pi}} \xi_i + \frac{1}{6\sqrt{2\pi}} \xi_i^3 \right)$$

subject to

$$x \geq 0$$

So far we have found it difficult to solve this class of nonlinear programming problems, but the day is not far when we can solve these problems. Further research will be continued by me in this direction and I would attempt to apply these optimization techniques to various industrial and national planning problems in Peru.

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State University, who unless they are aggressive or made warmly welcome, will never participate in the social life of the University.

9. APPENDIX A: PRODUCTION PLANNING - A COMPUTER PROGRAM



```

0042      II = L4 + 1
0043      DO 11 K = II,L5
0044      11 PB(K) = WORK
0045      K = L5 + 1
0046      PB(K) = SALMIN - XINVI
0047      IF(PB(K)) 12,13,13
0048      12 PB(K) = -PB(K)
0049      1333 = 1
0050      GO TO 14
0051      13 1333 = 0
0052      14 K = L5 + 2
0053      DO 15 I = K,L6
0054      15 PB(I) = SALMIN
0055      II = L6 + 1
0056      DO 16 K = II,L7
0057      16 PB(K) = YLOW
0058      II = L7 + 1
0059      DO 17 K = II,L8
0060      17 PB(K) = UPPY
0061      C      GENERATING THE RESTRICTION SUBMATRICES
0062      C      THE WORK FORCE RESTRICTION SUBMATRIX
0063      I = L4
0064      DO 18 J = 1,NTIME
0065      18 A(I,J) = 1.
0066      C      THE PRODUCTION CONSTRAINT MATRIX
0067      II = L5 + 1
0068      J = NTIME
0069      DO 19 I = II,L6
0070      19 A(I,J) = 1.
0071      J = L2
0072      18 = L5 + 2
0073      DO 20 I = 18,L6
0074      20 A(I,J) = 1.
0075      J = L3
0076      DO 21 I = II,L6
0077      21 A(I,J) = -XLAM
0078      IK = L3 + 1
0079      C      LOWER AND UPPER BOUND OF Y
0080      J = L2
0081      II = L6 + 1
0082      DO 22 I = II,L7
0083      22 A(I,J) = 1.
0084      J = L2
0085      IF(YLOW.LE.0) GO TO 230
0086      230 GO TO 232
0087      230 GO TO 232
0088      230 GO TO 232
0089      230 GO TO 232
0090      230 GO TO 232

```



```

0091      232 DO 23 I= 11,L8
0092      J = J + 1
0093      23 A(I,J) = 00
C      THE ARTIFICIAL MATRIX
0094      IN = L4 + 1
0095      DO 24 I = 1N,L7
0096      24 A(I,I) = -1.
0097      I = L5 + 1
0098      IF(I333 - 1) 27, 25, 27
0099      25 A(I,I) = 0.
0100      ISTAR = L5 + 1
0101      DO 26 I=NTIME,L4
0102      26 A(ISTAR,I) = -A(ISTAR,I)
0103      GO TO 28
0104      27 A(I,I) = -1
0105      29 CONTINUE
0106      IF(YLCW.NE.C) GO TO 291
0107      IQ = L6 + 1
0108      DO 280 I = IQ,L7
0109      280 A(I,I) = C.
0110      291 CONTINUE
C
C      *****
0111      WRITE(19,1919) ((A(I,J),J=1,L4),I=1,L4), (PB(I),I=1,L4)
0112      1919 FORMAT(4X,5D15.8)
C      SCALING
C      *****
0113      DO 5050 I=1,L4
0114      PB(I) = PB(I)/10.
0115      DO 5050 J = 1,L4
0116      5050 A(I,J) = A(I,J)/100.
0117      KX=L4 + 1
0118      DO 7070 J = 1,L4
0119      DO 7070 I = KX,L8
0120      7070 A(I,J) = A(I,J)/10.
C
C      -----
C      THE OUTPUT GENERATION
C
0121      IEND = L4 + 100
0122      J = 101
0123      WRITE(IND,29) (K, K=J,IEND)
0124      29 FORMAT( 'INPUT.      HMMS  ' /
1SCAN. ' /'ROW.ID      HMMS  ' /,(12X,'P',I3))
C      COMPLETING THE QUADRATIC MATRIX
0125      JF = L3 + 99
0126      WRITE(IND,31) (K, K=J,JF)
0127      31 FORMAT(12X,'A',I3)
0128      IF(I333.NE.0) GO TO 32
0129      JF = JF + 1
0130      WRITE(IND,31) JF
0131      32 IEND = L4 + 101
0132      IFIN = L5 + 100
0133      WRITE(IND,33) (K, K=IEND,IFIN)

```

```

0134      33 FORMAT(11X,'P',I3)
0135      K = IFIN + 1
0136      IF(I332 - 1) 34, 35, 34
0137      34 WRITE(IND,33) K
0138      GO TO 37
0139      35 WRITE(IND,36) K
0140      36 FORMAT(11X,'R',I3)
0141      37 IEND = IFIN + 2
0142      IF(YLOW.EQ.0) GO TO 38
0143      GO TO(39, 38), ICOND
0144      38 IFIN = L6 + 100
0145      GO TO 40
0146      39 IFIN = L7 + 100
0147      40 WRITE(IND,39) (K,K=IEND,IFIN)
0148      IEND = IFIN + 1
0149      IFIN = L8 + 100
0150      WRITE(IND,36) (K, K=IEND,IFIN)
0151      42 WRITE(IND,43)
0152      43 FORMAT('MATRIX')
0153      DO 46 J = 1,LE
0154      KCCL = 100 + J
0155      DO 46 I = 1,LE
0156      KROW = 100 + I
0157      IF(A(I,J)) 44, 46, 44
0158      44 WRITE(IND,45) KCCL,KROW, A(I,J)
0159      45 FORMAT(5X,'C',I3,2X,'R',I3,2X,F12.6)
0160      46 CONTINUE
0161      WRITE(IND,47)
0162      47 FORMAT('FIRST')
0163      DO 50 J = 1,LE
0164      KCCL = 100 + J
0165      IF(PB(J)) 48,50,48
0166      48 WRITE(IND,49) KCCL, PB(J)
0167      49 FORMAT(6X,'PB.',3X,'R',I3,2X,F12.6)
0168      50 CONTINUE
0169      WRITE(IND,51)
0170      51 FORMAT('ENDATA','MODEL','MAX...','OUTPUT','CHECK','INVERT','OUTPU
1T','ENDJOB')
0171      STOP
0172      END

```





A109	0.0
A110	0.0
A111	0.0
A112	0.0
A113	0.0
A114	0.0
A115	0.0
A116	0.0
A117	0.0
A118	0.0
A119	0.0
A120	0.0
A121	0.0
A122	0.0
A123	0.0
A124	0.0
A125	0.0
A126	0.0
A127	0.0
A128	0.0
A129	0.0
A130	0.0
A131	0.0
A132	0.0
A133	0.0
A134	0.0
A135	0.0
-P140	0.0
-P150	0.0
-P151	0.0
-P152	0.0
-P153	0.0
-P154	0.0
-P155	0.0
-P157	0.0
-P158	0.0
-P159	0.0
-P160	0.0
-P161	0.0
-P162	0.0
-P163	0.0
-P164	0.0
-P165	0.0
-P166	0.0
-P167	0.0
-P168	0.0
-P169	0.0
-P170	0.0
-P171	0.0
-P172	0.0
-P173	0.0
-P174	0.0
-P175	0.0
-P176	0.0
-P177	0.0
-P178	0.0
-P179	0.0
-P180	0.0
-P181	0.0
-P182	0.0

.....

C	-P183	C.0
C	-P184	C.0
C	+P185	0.0
C	+P186	0.0
C	+P187	C.0
C	+P188	0.0
C	+P189	C.0
C	+P190	C.0
C	+P191	C.0
C	+P192	C.0
C	+P193	C.0
C	+P194	C.0
C	+P195	C.0
C	+P196	C.0

	MATRIX		
C	C101	P101	-2.160474
C	C101	P102	1.028798
C	C101	P113	0.018144
C	C101	P140	0.100000
C	C102	P101	1.028798
C	C102	P102	-2.160474
C	C102	P103	1.028798
C	C102	P114	0.018144
C	C102	P150	0.100000
C	C103	P102	1.028798
C	C103	P103	-2.160474
C	C103	P104	1.028798
C	C103	P115	0.018144
C	C103	P151	0.100000
C	C104	P103	1.028798
C	C104	P104	-2.160474
C	C104	P105	1.028798
C	C104	P116	0.018144
C	C104	P152	0.100000
C	C105	P104	1.028798
C	C105	P105	-2.160474
C	C105	P106	1.028798
C	C105	P117	0.018144
C	C105	P153	0.100000
C	C105	P105	1.028798
C	C106	P106	-2.160474
C	C106	P107	1.028798
C	C106	P118	0.018144
C	C106	P154	0.100000
C	C107	P106	1.028798
C	C107	P107	-2.160474
C	C107	P108	1.028798
C	C107	P119	0.018144
C	C107	P155	0.100000
C	C108	P107	1.028798
C	C108	P108	-2.160474
C	C108	P109	1.028798
C	C108	P120	0.018144
C	C108	P156	0.100000
C	C109	P108	1.028798
C	C109	P109	-2.160474
C	C109	P110	1.028798
C	C109	P121	0.018144
C	C109	P157	0.100000
C	C110	P109	1.028798

C110	q110	-2.160474
C110	q111	1.028799
C110	q122	0.018144
C110	q158	0.100000
C111	q110	1.028799
C111	q111	-2.160474
C111	q112	1.028799
C111	q123	0.018144
C111	q159	0.100000
C112	q111	1.028799
C112	q112	-1.131676
C112	q124	0.018144
C112	q160	0.100000
C113	q101	0.018144
C113	q113	-0.003200
C113	q161	-0.100000
C114	q102	0.018144
C114	q114	-0.003200
C114	q162	0.100000
C115	q103	0.018144
C115	q115	-0.003200
C115	q163	0.100000
C116	q104	0.018144
C116	q116	-0.003200
C116	q164	0.100000
C117	q105	0.018144
C117	q117	-0.003200
C117	q165	0.100000
C118	q106	0.018144
C118	q118	-0.003200
C118	q166	0.100000
C119	q107	0.018144
C119	q119	-0.003200
C119	q167	0.100000
C120	q108	0.018144
C120	q120	-0.003200
C120	q168	0.100000
C121	q109	0.018144
C121	q121	-0.003200
C121	q169	0.100000
C122	q110	0.018144
C122	q122	-0.003200
C122	q170	0.100000
C123	q111	0.018144
C123	q123	-0.003200
C123	q171	0.100000
C124	q112	0.018144
C124	q124	-0.003200
C124	q172	0.100000
C125	q125	-0.001320
C125	q162	0.100000
C126	q126	-0.001320
C126	q163	0.100000
C127	q127	-0.001320
C127	q164	0.100000
C128	q128	-0.001320
C128	q165	0.100000
C129	q129	-0.001320
C129	q166	0.100000
C130	q130	-0.001320
C130	q167	0.100000

c	c131	0131	-0.001320
c	c131	016A	0.100000
c	c132	0132	-0.001320
c	c132	0169	0.100000
c	c133	0133	-0.001320
c	c133	0170	0.100000
c	c134	0134	-0.001320
c	c134	0171	0.100000
c	c135	0135	-0.001320
c	c135	0172	0.100000
c	c136	0136	-0.001320
c	c137	0161	20.000000
c	c137	0173	0.100000
c	c137	0185	0.100000
c	c138	0162	-20.000000
c	c138	0174	0.100000
c	c138	0186	0.100000
c	c139	0163	-20.000000
c	c139	0175	0.100000
c	c139	0187	0.100000
c	c140	0164	-20.000000
c	c140	0176	0.100000
c	c140	0188	0.100000
c	c141	0165	-20.000000
c	c141	0177	0.100000
c	c141	0189	0.100000
c	c142	0166	-20.000000
c	c142	0178	0.100000
c	c142	0190	0.100000
c	c143	0167	-20.000000
c	c143	0179	0.100000
c	c143	0191	0.100000
c	c144	0168	-20.000000
c	c144	0180	0.100000
c	c144	0192	0.100000
c	c145	0169	-20.000000
c	c145	0181	0.100000
c	c145	0193	0.100000
c	c146	0170	-20.000000
c	c146	0182	0.100000
c	c146	0194	0.100000
c	c147	0171	-20.000000
c	c147	0183	0.100000
c	c147	0195	0.100000
c	c148	0172	-20.000000
c	c148	0184	0.100000
c	c148	0196	0.100000
c	c149	0149	-1.000000
c	c150	0150	-1.000000
c	c151	0151	-1.000000
c	c152	0152	-1.000000
c	c153	0153	-1.000000
c	c154	0154	-1.000000
c	c155	0155	-1.000000
c	c156	0156	-1.000000
c	c157	0157	-1.000000
c	c158	0158	-1.000000
c	c159	0159	-1.000000
c	c160	0160	-1.000000
c	c162	0162	-1.000000
c	c163	0163	-1.000000



0	C164	P164	-1.000000
0	C165	P165	-1.000000
0	C166	P166	-1.000000
0	C167	P167	-1.000000
0	C168	P168	-1.000000
0	C169	P169	-1.000000
0	C170	P170	-1.000000
0	C171	P171	-1.000000
0	C172	P172	-1.000000
0	C173	P173	-1.000000
0	C174	P174	-1.000000
0	C175	P175	-1.000000
0	C176	P176	-1.000000
0	C177	P177	-1.000000
0	C178	P178	-1.000000
0	C179	P179	-1.000000
0	C180	P180	-1.000000
0	C181	P181	-1.000000
0	C182	P182	-1.000000
0	C183	P183	-1.000000
0	C184	P184	-1.000000

FIRSTB

0	PR.	P101	-921.190463
0	PR.	P102	22.055969
0	PR.	P103	22.055969
0	PR.	P104	22.055969
0	PR.	P105	22.055969
0	PR.	P106	22.055969
0	PR.	P107	22.055969
0	PR.	P108	22.055969
0	PR.	P109	22.055969
0	PR.	P110	22.055969
0	PR.	P111	22.055969
0	PR.	P112	22.055969
0	PR.	P113	4.095999
0	PR.	P114	4.095999
0	PR.	P115	4.095999
0	PR.	P116	4.095999
0	PR.	P117	4.095999
0	PR.	P118	4.095999
0	PR.	P119	4.095999
0	PR.	P120	4.095999
0	PR.	P121	4.095999
0	PR.	P122	4.095999
0	PR.	P123	4.095999
0	PR.	P124	4.095999
0	PR.	P125	-4.223996
0	PR.	P126	-4.223996
0	PR.	P127	-4.223996
0	PR.	P128	-4.223996
0	PR.	P129	-4.223996
0	PR.	P130	-4.223996
0	PR.	P131	-4.223996
0	PR.	P132	-4.223996
0	PR.	P133	-4.223996
0	PR.	P134	-4.223996
0	PR.	P135	-4.223996
0	PR.	P136	-4.223996
0	PR.	P137	-0.020000
0	PR.	P138	-0.020000

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C	PR.	0140	-0.020000
C	PR.	0141	-0.020000
C	PR.	0142	-0.020000
C	PR.	0143	-0.020000
C	PR.	0144	-0.020000
C	PR.	0145	-0.020000
C	PR.	0146	-0.020000
C	PR.	0147	-0.020000
C	PR.	0148	-0.020000
C	PR.	0149	75.000000
C	PR.	0150	75.000000
C	PR.	0151	75.000000
C	PR.	0152	75.000000
C	PR.	0153	75.000000
C	PR.	0154	75.000000
C	PR.	0155	75.000000
C	PR.	0156	75.000000
C	PR.	0157	75.000000
C	PR.	0158	75.000000
C	PR.	0159	75.000000
C	PR.	0160	75.000000
C	PR.	0161	20.000000
C	PR.	0162	300.000000
C	PR.	0163	300.000000
C	PR.	0164	300.000000
C	PR.	0165	300.000000
C	PR.	0166	300.000000
C	PR.	0167	300.000000
C	PR.	0168	300.000000
C	PR.	0169	300.000000
C	PR.	0170	300.000000
C	PR.	0171	300.000000
C	PR.	0172	300.000000
C	PR.	0173	2.659260
C	PR.	0174	2.659260
C	PR.	0175	2.659260
C	PR.	0176	2.659260
C	PR.	0177	2.659260
C	PR.	0178	2.659260
C	PR.	0179	2.659260
C	PR.	0180	2.659260
C	PR.	0181	2.659260
C	PR.	0182	2.659260
C	PR.	0183	2.659260
C	PR.	0184	2.659260
C	PR.	0185	2.659260
C	PR.	0186	2.659260
C	PR.	0187	2.659260
C	PR.	0188	2.659260
C	PR.	0189	2.659260
C	PR.	0190	2.659260
C	PR.	0191	2.659260
C	PR.	0192	2.659260
C	PR.	0193	2.659260
C	PR.	0194	2.659260
C	PR.	0195	2.659260
C	PR.	0196	2.659260

ENDATA

NUMBER ROWS IN A	VARIABLES	PHS	DENSITY
48	83	1	294

AGENDUM TIME WAS 0.183 MINUTES





119	20119	R184...	30119	R184...	93	1.0000	49	-0.1000
120	20120	R185...	30120	R185...	37	-0.1000	49	-0.1000
121	20121	R186...	30121	R186...	38	-0.1000	49	-0.1000
122	20122	R187...	30122	R187...	39	-0.1000	49	-0.1000
123	20123	R188...	30123	R188...	40	-0.1000	49	-0.1000
124	20124	R189...	30124	R189...	41	-0.1000	49	-0.1000
125	20125	R190...	30125	R190...	42	-0.1000	49	-0.1000
126	20126	R191...	30126	R191...	43	-0.1000	49	-0.1000
127	20127	R192...	30127	R192...	44	-0.1000	49	-0.1000
128	20128	R193...	30128	R193...	45	-0.1000	49	-0.1000
129	20129	R194...	30129	R194...	46	-0.1000	49	-0.1000
130	20130	R195...	30130	R195...	47	-0.1000	49	-0.1000
131	20131	R196...	30131	R196...	48	-0.1000	49	-0.1000

AGENDUM TIME WAS 0.022 MINUTES

PAY... DEDUCTION ACCOUNTING									
DEDUCTION ACCOUNTING 1.000									
LINE	ENTER	BASIS	LEAVE	7J-CJ S	B	NB	INFEAS		
1	10001	84	20084	-35	0	0	4154.91112	43	101
2	20084	1	40001	-35	1	84	4156.91112	46	101
3	10002	85	20085		0	0	4081.91112	54	101
4	20085	2	40002		2	85	4081.91112	57	101
5	10003	86	20086	0	0	0	4006.91112	56	101
6	20086	3	40003	0	3	86	4006.91112	68	101
7	10004	87	20087	0	0	0	3931.91112	74	101
8	20087	4	40004	0	4	87	3931.91112	79	101
9	10005	88	20088	0	0	0	3856.91112	87	101
10	20088	5	40005	0	5	88	3856.91112	90	101
11	10006	89	20089	0	0	0	3781.91112	98	101
12	20089	6	40006	0	0	0	3781.91112	101	101
13	10007	90	20090	0	0	0	3706.91112	109	101
14	20090	7	40007	0	7	90	3706.91112	112	101
15	10008	91	20091	-28	0	0	3631.91112	120	101
16	20091	8	40008	-28	8	91	3631.91112	123	101
17	10009	92	20092	0	0	0	3556.91112	131	101
18	20092	9	40009	0	0	0	3556.91112	134	101
19	10010	93	20093	0	0	0	3481.91112	142	101
20	20093	10	40010	0	10	93	3481.91112	145	101
21	10011	94	20094	0	0	0	3406.91112	153	101
22	20094	11	40011	0	11	94	3406.91112	156	101
23	10012	95	20095	0	0	0	3331.91112	163	101
24	20095	12	40012	0	12	95	3331.91112	166	101
25	10014	97	20097	0	0	0	3031.91112	172	101
26	20097	14	40014	0	14	97	3031.91112	177	101
27	10015	98	20098	0	0	0	2731.91112	183	101
28	20098	15	40015	0	15	98	2731.91112	186	101
29	10016	99	20099	-21	0	0	2431.91112	194	101
30	20099	16	40016	-21	16	99	2431.91112	199	101
31	10017	100	20100	0	0	0	2131.91112	205	101
32	20100	17	40017	0	17	100	2131.91112	210	101
33	10018	101	20101	0	0	0	1831.91112	216	101
34	20101	18	40018	0	18	101	1831.91112	221	101
35	10019	102	20102	0	0	0	1531.91112	227	101
36	20102	19	40019	0	19	102	1531.91112	232	101
37	10020	103	20103	0	0	0	1231.91112	238	101
38	20103	20	40020	0	20	103	1231.91112	243	101
39	10021	104	20104	0	0	0	931.91112	249	101
40	20104	21	40021	0	21	104	931.91112	254	101
41	10022	105	20105	0	0	0	631.91112	260	101
42	20105	22	40022	0	22	105	631.91112	265	101
43	10023	106	20106	-14	0	0	331.91112	271	101
44	20106	23	40023	-14	23	106	331.91112	276	101
45	10024	107	20107	0	0	0	31.91112	282	101
46	20107	24	40024	0	24	107	31.91112	287	101
47	10037	06	20096	0	0	0	31.81112	292	101
48	20096	37	40037	0	37	06	31.81112	296	101
49	10038	109	20109	-12	0	0	29.15186	306	101
50	20109	38	40038	-12	38	109	29.15186	309	101
51	10039	110	20110	1	0	0	26.49260	320	101
52	20110	39	40039	1	39	110	26.49260	323	101
53	10040	111	20111	1	0	0	23.83334	334	101
54	20111	40	40040	1	40	111	23.83334	337	101

55	10041	112	20112	1	0	0	21,17408	248	101	-C,10000
56	30112	41	40041	1	41	112	21,17408	251	101	-C,10000
57	10042	113	20113	1	0	0	18,51492	262	101	-C,10000
58	30113	42	40042	1	42	113	18,51492	265	101	-C,10000
59	10043	114	20114	1	0	0	15,85556	276	101	-C,10000
60	30114	43	40043	1	43	114	15,85556	279	101	-C,10000
61	10044	115	20115	1	0	0	13,19630	290	101	-C,10000
62	30115	44	40044	1	44	115	13,19630	293	101	-C,10000
63	10045	116	20116	-5	0	0	10,53704	404	101	-C,10000
64	30116	45	40045	-5	45	116	10,53704	407	101	-C,10000
65	10046	117	20117	1	0	0	7,87778	418	101	-C,10000
66	30117	46	40046	1	46	117	7,87778	421	101	-C,10000
67	10047	118	20118	1	0	0	5,21852	432	101	-C,10000
68	30118	47	40047	1	47	118	5,21852	435	101	-C,10000
69	10048	119	20119	1	0	0	2,55926	446	101	-C,10000
70	30119	48	40048	1	48	119	2,55926	449	101	-C,10000
71	10013	109	20108	-1	0	0	-0,0	457	101	-C,00050
72	30108	13	40013	-1	13	108	-0,0	451	101	-C,00050

SOLUTION RESULTS

ITERATION TIME WAS 0.096 MINUTES







PRIMAL SLACKS		OPT. LEVEL	
p105	20120	1	0.0
p104	20121	1	0.0
p107	20122	1	0.0
p100	20123	1	0.0
p103	20124	1	0.0
p106	20125	1	0.0
p101	20126	1	0.0
p102	20127	1	0.0
p108	20128	1	0.0
p104	20129	1	0.0
p105	20130	1	0.0
p106	20131	1	0.0

LAGRANGE MULT.		OPT. LEVEL	
p140	30094	-1	0.0
p150	30085	-1	0.0
p151	30096	-1	-0.505615750 02
p152	30097	-1	-0.339100480 03
p153	30098	-1	-0.339100480 03
p154	30089	-1	-0.339100480 03
p155	30090	-1	-0.339100480 03
p156	30091	-1	-0.339100480 03
p157	30092	-1	-0.339100480 03
p158	30093	-1	-0.339100480 03
p159	30094	-1	-0.339100480 03
p160	30095	-1	-0.339100480 03
p161	30096	1	0.523663010 02
p162	30097	-1	-0.185688190 02
p163	30098	-1	-0.200549000 02
p164	30099	-1	-0.200549000 02
p165	30100	-1	-0.200549000 02
p166	30101	-1	-0.200549000 02
p167	30102	-1	-0.200549000 02
p168	30103	-1	-0.200549000 02
p169	30104	-1	-0.200549000 02
p170	30105	-1	-0.200549000 02
p171	30106	-1	-0.200549000 02
p172	30107	-1	-0.200549000 02
p173	30108	-1	-0.194730640 05
p174	30109	-1	-0.371356510 04
p175	30110	-1	-0.401078150 04
p176	30111	-1	-0.401078150 04
p177	30112	-1	-0.401078150 04
p178	30113	-1	-0.401078150 04
p179	30114	-1	-0.401078150 04
p180	30115	-1	-0.401078150 04
p181	30116	-1	-0.401078150 04
p182	30117	-1	-0.401078150 04
p183	30118	-1	-0.401078150 04
p184	30119	-1	-0.401078150 04

LAGRANGE SLACK		OPT. LEVEL	
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A103	40051	0.505615750 02
A104	40052	0.339100480 03
A105	40053	0.339100480 03
A106	40054	0.339100480 03
A107	40055	0.339100480 03
A108	40056	0.339100480 03
A109	40057	0.339100480 03
A110	40058	0.339100480 03
A111	40059	0.339100480 03
A112	40060	0.339100480 03
A113	40061	0.185682190 02
A114	40062	0.200549000 02
A115	40063	0.200549000 02
A116	40064	0.200549000 02
A117	40065	0.200549000 02
A118	40066	0.200549000 02
A119	40067	0.200549000 02
A120	40068	0.200549000 02
A121	40069	0.200549000 02
A122	40070	0.200549000 02
A123	40071	0.200549000 02
A124	40072	0.104730640 05
A125	40073	0.371356510 04
A126	40074	0.401078150 04
A127	40075	0.401078150 04
A128	40076	0.401078150 04
A129	40077	0.401078150 04
A130	40078	0.401078150 04
A131	40079	0.401078150 04
A132	40080	0.401078150 04
A133	40081	0.401078150 04
A134	40082	0.401078150 04
A135	40083	0.401078150 04

FUNCTIONAL VALUE IS 0.990431180 05

AGENDUM TIME WAS 0.074 MINUTES

CHECK		NAME	ORIGINAL PHS	SOLUTION VALUE	P7W ERQR
P7W					
1		P101	-921.199463	-921.199463	-0.000000
2		P102	22.055969	22.055969	0.000000
3		P103	22.055969	22.055969	0.000000
4		P104	22.055969	22.055969	-0.000000
5		P105	22.055969	22.055969	0.000000
6		P106	22.055969	22.055969	0.000000
7		P107	22.055969	22.055969	0.000000
8		P108	22.055969	22.055969	-0.000000
9		P109	22.055969	22.055969	0.000000
10		P110	22.055969	22.055969	-0.000000
11		P111	22.055969	22.055969	0.000000
12		P112	22.055969	22.055969	0.000000
13		P113	4.095999	4.095999	0.000000
14		P114	4.095999	4.095999	0.000000
15		P115	4.095999	4.095999	0.000000
16		P116	4.095999	4.095999	0.000000
17		P117	4.095999	4.095999	0.000000
18		P118	4.095999	4.095999	-0.000000
19		P119	4.095999	4.095999	0.000000
20		P120	4.095999	4.095999	0.000000
21		P121	4.095999	4.095999	0.000000
22		P122	4.095999	4.095999	0.000000
23		P123	4.095999	4.095999	0.000000
24		P124	4.095999	4.095999	0.000000
25		P125	-4.223996	-4.223996	0.000000
26		P126	-4.223996	-4.223996	0.000000
27		P127	-4.223996	-4.223996	0.000000
28		P128	-4.223996	-4.223996	0.000000
29		P129	-4.223996	-4.223996	0.000000
30		P130	-4.223996	-4.223996	-0.000000
31		P131	-4.223996	-4.223996	0.000000
32		P132	-4.223996	-4.223996	0.000000
33		P133	-4.223996	-4.223996	0.000000
34		P134	-4.223996	-4.223996	0.000000
35		P135	-4.223996	-4.223996	0.000000
36		P136	-4.223996	-4.223996	0.000000
37		P137	-0.020000	-0.020000	0.000000
38		P138	-0.020000	-0.020000	0.000000
39		P139	-0.020000	-0.020000	0.000000
40		P140	-0.020000	-0.020000	0.000000
41		P141	-0.020000	-0.020000	0.000000
42		P142	-0.020000	-0.020000	0.000000
43		P143	-0.020000	-0.020000	0.000000
44		P144	-0.020000	-0.020000	0.000000
45		P145	-0.020000	-0.020000	0.000000
46		P146	-0.020000	-0.020000	0.000000
47		P147	-0.020000	-0.020000	0.000000
48		P148	-0.020000	-0.020000	0.000000
49		A101	0.0	0.0	0.0
50		A102	0.0	0.0	0.0
51		A103	0.0	0.000000	-0.000000
52		A104	0.0	0.000000	-0.000000
53		A105	0.0	0.000000	-0.000000
54		A106	0.0	0.000000	-0.000000
55		A107	0.0	0.000000	-0.000000
56		A108	0.0	0.0	0.0



118	0193	2.659260	2.659260	0.000000
119	0184	2.659260	2.659260	0.000000
120	0195	2.659260	2.659260	0.000000
121	0186	2.659260	2.659260	0.000000
122	0187	2.659260	2.659260	0.000000
123	0188	2.659260	2.659260	0.000000
124	0189	2.659260	2.659260	0.000000
125	0190	2.659260	2.659260	0.000000
126	0191	2.659260	2.659260	0.000000
127	0192	2.659260	2.659260	0.000000
128	0193	2.659260	2.659260	0.000000
129	0194	2.659260	2.659260	0.000000
130	0195	2.659260	2.659260	0.000000
131	0196	2.659260	2.659260	0.000000

MAXIMUM ERROR IN RW 47 0.12555555555555555

AGGREGATE TIME WAS 7.735 MINUTES

INVERT            PRICING FRACTION 1.000  
ITERATION ACCOUNTING  
ITD    ENTER   BASIS   LEAVE   7J-CJ S   B   NB   INFEAS

INVERT TIME WAS 0.036 MINUTES.

SOLUTION FEASIBLE.

..

SOLUTION OPTIMAL.

AGENDUM TIME WAS 0.173 MINUTES



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FORTRAN IV C LEVEL 1, MOD 4                      MAIN                      DATE = 69293                      16/56/28                      PAGE 0001

```

      VALUE OF THE OBJECTIVE FUNCTION
0001      DOUBLE PRECISION A(48,48),R(48), X(128),V1,V2,V3,DV1,DV2,TVAL
0002      DATA V1,V2,V3/0.,0.,0./,X/128*0./
0003      READ(10,1) INO, NTIME,ICONO,SCALE
0004      1 FORMAT(3I3,F12.4)
0005      READ(10,20) C1,C2,C3,C4,C5,C6,C7,C8,C9,PAR1,
      W1,W2,WOR1, XINVT,WORK,UPPY,YLOW,PAR2
0006      20 FORMAT((F612.4))
0007      L3 = 3*NTIME
0008      L4 = 4*NTIME
0009      READ(10,21) ((A(I,J), J=1,L4), I=1,L4), (R(I), I=1,L4)
0010      21 FORMAT(4X,F015.8)
0011      READ(20,3,END=4) (IX,X(IX), J=1,128)
0012      3 FORMAT(4X,I2,10X,F15.8)
0013      4 WRITE(2,60) NTIME, W1, W2, C1,C2,C3,C4,C5,C6,C7,C8,C9,WOR1,WORK,
      XINVT, PAR1,PAR2, UPPY, YLOW,SCALE
0014      60 FORMAT('1',50X,'THE PROBLEM PARAMETER ARE','0',30X,'NTIME = ', I5,
      '1',10X,'W1 = ',F14.8,10X,'W2 = ',F14.8/'0',20X,'C1 = ',F14.
      2,8,10X,'C2 = ',F14.8,10X,'C3 = ',F14.8/'0',30X,'C4 = ',F14.
      34,8,10X,'C5 = ',F14.8,10X,'C6 = ',F14.8/'0',30X,'C7 = ',F14.
      414,8,10X,'C8 = ',F14.8,10X,'C9 = ',F14.8/'0',30X,'INT WOR = ',F1
      54,8,10X,'WOR DEC = ',F14.8,10X,'INT INV = ',F14.8/'0',40X,'AVER SALE
      6 = ',F14.8,10X,'MIN SALE = ',F14.8/'0',40X,'UPPER Y = ',F14.8,15X,'
      7LOWER Y = ',F14.8/'0',60X,'SCALE = ',F15.8////)
0015      DO 5 K=1,L4
0016      X(K) = X(K)/SCALE
0017      DO 5 J=1,L4
0018      5 A(I,J) = +A(I,J)*.5
0019      DO 6 I=1,L3
0020      V2 = V2 - X(I)*A(I)
0021      DO 6 J=1,L3
0022      6 V1 = V1 + X(I)*X(J)*A(I,J)
0023      IP = L3 +1
0024      DO 7 I=IP,L4
0025      7 V3 = V3 - X(I)*R(I)
0026      DV1 = -V1/W1
0027      DV2 = -V2/W1
0028      TVAL = DV1 + DV2
0029      DV3 = -V3/W2
      EVALUATION OF CONSTANT TERM
0030      CC = 24.*C7*C8*CO*PAR1 + 12.*C7*CR**2 + C2*WOR1
0031      COST=TVAL+CC
0032      WRITE(3,9) ( I,X(I), X(I+NTIME),X(I+2*NTIME),X(I+L3),I=1,NTIME)
0033      9 FORMAT('0',////60X,'THE RESULTS'////'0',15X,'PERIOD',8X,'WORK LEV
      1EL',10X,'PRODUCTION LEVEL',7X,'INVENTORY LEVEL',7X,'RELIABILITY LE
      2VEL'////'0',17X,12,4(RX,F15.8)))
0034      WRITE(3,10) COST,CC,DV1
0035      WRITE(3,11) DV2,TVAL,DV3
0036      10 FORMAT('0',
      35X,'FIXED COST = ',D15.8, 5X,'QUADRATIC COST = ',D15.8)
0037      11 FORMAT('0',
      4 COST = ',D15.8,5X,'VARIABLE COST = ',D15.8, 5X,'RELIABILITY
      5COST = ',D15.8/'0',50X,'-----')

```

THE PROBLEM PARAMETER ARE

NTIME = 12            W1 = 0.79999995E 00            W2 = 0.19999999E 00  
 C1 = 0.34000000E 03            C2 = 0.64299988E 02            C3 = 0.19999999E 00  
 C4 = 0.56699991E 01            C5 = 0.51199997E 02            C6 = 0.28100000E 03  
 C7 = 0.82499981E-01            C8 = 0.32000000E 03C9 = 0.0  
 INT WOR = 0.90000000E 02            WOR RES = 0.75000000E 02            INT INV = 0.32000000E 03  
 AVER SALE = 0.50000000E 03            MIN SALE = 0.30000000E 03  
 UPPER Y = 0.26589994E 01            LOWER Y = 0.26589994E 01  
 SCALE = 0.10000000E 02

THE RESULTS

PERIOD	WORK LEVEL	PRODUCTION LEVEL	INVENTORY LEVEL	RELIABILITY LEVEL
1	0.83987255D 02	0.51185233D 03	0.46067260D 03	0.26592607D 01
2	0.77804647D 02	0.37117985D 03	0.47193079D 03	0.26592607D 01
3	0.75000027D 02	0.35992166D 03	0.47193079D 03	0.26592607D 01
4	0.75000027D 02	0.35992166D 03	0.47193079D 03	0.26592607D 01
5	0.75000027D 02	0.35992166D 03	0.47193079D 03	0.26592607D 01
6	0.75000027D 02	0.35992166D 03	0.47193079D 03	0.26592607D 01
7	0.75000027D 02	0.35992166D 03	0.47193079D 03	0.26592607D 01
8	0.75000027D 02	0.35992166D 03	0.47193079D 03	0.26592607D 01
9	0.75000027D 02	0.35992166D 03	0.47193079D 03	0.26592607D 01
10	0.75000027D 02	0.35992166D 03	0.47193079D 03	0.26592607D 01
11	0.75000027D 02	0.35992166D 03	0.47193079D 03	0.26592607D 01
12	0.75000027D 02	0.35992166D 03	0.31999976D 03	0.26592607D 01

TOTAL COST = 0.65934750E C6      FIXED COST = 0.10716287E 06      QUADRATIC COST = 0.13519795D 07  
LINEAR COST = -0.79979482D 06      VARIABLE COST = 0.55218463D 06      RELIABILITY COST = -0.31911118E 02

-----  
SUMMARY OF ERRORS FOR THIS JOB      ERROR NUMBER      NUMBER OF ERRORS  
217      1

## 10. APPENDIX B: A NONLINEAR PROGRAMMING SOLUTION

Our problem is

$$\begin{aligned} \text{Min } f(\bar{x}) \equiv & -.05(x_1+x_2+x_3) - \ln x_4 - \ln x_5 - \ln x_6 \\ & - \ln x_7 - \ln x_8 \end{aligned}$$

subject to

$$\begin{aligned} g_1(\bar{x}) &\equiv 1300 + (.05-.15x_4)x_1 && \geq 0 \\ g_2(\bar{x}) &\equiv 1000 + (.05-.15x_5)x_2 && \geq 0 \\ g_3(\bar{x}) &\equiv 1000 + (.05-.15x_6)x_3 && \geq 0 \\ g_4(\bar{x}) &\equiv 7000 - x_1 && \geq 0 \\ g_5(\bar{x}) &\equiv 5500 + (.05-.15x_7)x_1 && \geq 0 \\ g_6(\bar{x}) &\equiv -.15x_8\sqrt{x_1^2+x_2^2} + 9000 + .05x_1 + .05x_2 - x_3 && \geq 0 \\ g_7(\bar{x}) &\equiv x_4x_5x_6x_7x_8^{-1.29^5} && \geq 0 \\ g_8(\bar{x}) &\equiv 4.-x_4 && \geq 0 \\ g_9(\bar{x}) &\equiv 4.-x_5 && \geq 0 \\ g_{10}(\bar{x}) &\equiv 4.-x_6 && \geq 0 \\ g_{11}(\bar{x}) &\equiv 4.-x_7 && \geq 0 \\ g_{12}(\bar{x}) &\equiv 4.-x_8 && \geq 0 \end{aligned}$$

The program AUKLET (126) modified by the author uses sequential unconstrained minimization technique (SUMT) developed by V. Fiacco and G. P. McCormick (82).

Three additional subroutines are needed before the program is executable. These three FORTRAN IV subroutines are written by the user and are:

RESTNT defines the values of  $f(\bar{x})$  and  $g_i(\bar{x})$

GRAD1 defines the first derivatives of  $f(\bar{x})$  and  $f_i(\bar{x})$

MATRIX defines the partial derivatives of  $f(\bar{x})$  and  $g_i(\bar{x})$

So we must supply the following system of equations

For RESTNT subroutine

$$f(\bar{x}) = -.05(x_1 + x_2 + x_3) - \sum_{k=4}^8 \ln x_k$$

$$g_1(\bar{x}) = 1000 + (.05 - .15x_4)x_1$$

$$g_2(\bar{x}) = 1000 + (.05 - .15x_5)x_2$$

$$g_3(\bar{x}) = 1000 + (.05 - .15x_6)x_3$$

$$g_4(\bar{x}) = 7000 - x_1$$

$$g_5(\bar{x}) = 5500 + (.05 - .15x_7)x_1 - x_2$$

$$g_6(\bar{x}) = -.15(x_8 \sqrt{x_1^2 + x_2^2} + 9000 + .05x_1 + .05x_2 - x_3)$$

$$g_7(\bar{x}) = x_4 x_5 x_6 x_7 x_8 - (1.29)^5$$

$$g_8(\bar{x}) = 4 - x_4$$

$$g_9(\bar{x}) = 4 - x_5$$

$$g_{10}(\bar{x}) = 4 - x_6$$

$$g_{11}(\bar{x}) = 4 - x_7$$

$$g_{12}(\bar{x}) = 4 - x_8$$

For GRAD1 subroutine

We evaluate the first derivatives

For  $f(\bar{x})$

$$\frac{\partial f(\bar{x})}{\partial x_i} = -.05 \quad i=1,2,3$$

$$\frac{\partial f(\bar{x})}{\partial x_i} = -\frac{1}{x_i} \quad i=4,5,6,7,8$$

For  $g_1(\bar{x})$

$$\frac{\partial g_1(\bar{x})}{\partial x_1} = .05 - .15x_4 \quad \frac{\partial g_1(\bar{x})}{\partial x_4} = -.15x_1 \quad \frac{\partial g_1(\bar{x})}{\partial x_k} = 0$$

for  $k \neq 1$  or  $4$

For  $g_2(\bar{x})$

$$\frac{\partial g_2(\bar{x})}{\partial x_2} = .05 - .15x_4 \quad \frac{\partial g_2(\bar{x})}{\partial x_5} = .15x_2 \quad \frac{\partial g_2(\bar{x})}{\partial x_k} = 0$$

for  $k \neq 2$  or  $5$

For  $g_3(\bar{x})$

$$\frac{\partial g_3(\bar{x})}{\partial x_3} = .05 - .15x_6 \quad \frac{\partial g_3(\bar{x})}{\partial x_6} = -.15x_3 \quad \frac{\partial g_3(\bar{x})}{\partial x_k} = 0$$

for any  $k \neq 3$  or  $6$

For  $g_4(\bar{x})$

$$\frac{\partial g_4(\bar{x})}{\partial x_1} = -1 \quad \frac{\partial g_4(\bar{x})}{\partial x_k} = 0 \quad \text{for any } k \neq 1$$

For  $g_5(\bar{x})$

$$\frac{\partial g_5(\bar{x})}{\partial x_7} = .05 - .15x_7 \quad \frac{\partial g_5(\bar{x})}{\partial x_2} = -1 \quad \frac{\partial g_5(\bar{x})}{\partial x_1} = -.15x_1$$

$$\frac{\partial g_5(\bar{x})}{\partial x_k} = 0 \quad \text{for any } k \neq 1, 2, \text{ or } 7$$

For  $g_6(\bar{x})$

$$\frac{\partial g_6(\bar{x})}{\partial x_1} = \frac{-.05x_8x_1}{\sqrt{x_1^2 + x_2^2}} + .05 \quad \frac{\partial g_6(\bar{x})}{\partial x_2} = \frac{-.05x_8x_2}{\sqrt{x_1^2 + x_2^2}} + .05$$

$$\frac{\partial g_6(\bar{x})}{\partial x_3} = -1 \quad \frac{\partial g_6(\bar{x})}{\partial x_3} = -.05\sqrt{x_1^2 + x_2^2} \quad \frac{\partial g_6(\bar{x})}{\partial x_k} = 0$$

for  $k = 4, 5, 6, 7$

For  $g_7(\bar{x})$

$$\frac{\partial g_7(\bar{x})}{\partial x_k} = 0 \quad \text{for } k = 1, 2, 3$$

$$\frac{\partial g_7(\bar{x})}{\partial x_k} = \frac{x_4x_5x_6x_7x_8}{x_k} \quad \text{for } k = 4, 5, 6, 7, 8$$



For  $g_j(\bar{x})$   $j=8,9,10,11,12$

$$\frac{\partial g_j(\bar{x})}{\partial x_k} = -1. \quad \text{for } j=k; k=4,5,6,7,8$$

For MATRIX subroutine

We evaluate the partial derivatives of  $f(\bar{x})$  and  $g_i(x)$ .

For  $f(\bar{x})$

$$\frac{\partial^2 f(\bar{x})}{\partial x_k^2} = 1/x_k^2 \quad k=4,5,6,7,8$$

$$\frac{\partial^2 f(\bar{x})}{\partial x_i^2} = 0 \quad i=1,2,3$$

$$\frac{\partial^2 f(\bar{x})}{\partial x_i \partial x_j} = 0 \quad i=1,\dots,8 \quad j=1,\dots,8$$

For  $g_1(\bar{x})$

$$\frac{\partial^2 g_1(\bar{x})}{\partial x_i \partial x_j} = 0 \quad i=j; i,j \neq 1,4; i=1,\dots,8; j=1,\dots,8$$

$$\frac{\partial^2 g_1(\bar{x})}{\partial x_1 \partial x_4} = \frac{\partial^2 g_1(\bar{x})}{\partial x_4 \partial x_1} = -.15$$

For  $g_2(\bar{x})$

$$\frac{\partial^2 g_2(\bar{x})}{\partial x_i \partial x_j} = 0 \quad i=j; i,j \neq 2,5; i=1,\dots,8; j=1,\dots,8$$

$$\frac{\partial^2 g_2(\bar{x})}{\partial x_2 \partial x_5} = \frac{\partial^2 g_2(\bar{x})}{\partial x_5 \partial x_2} = -.15$$

For  $g_3(\bar{x})$

$$\frac{\partial^2 g_3(\bar{x})}{\partial x_i \partial x_j} = 0 \quad i=j; \quad i, j \neq 3, 6; \quad i=1, \dots, 8; \quad j=1, \dots, 8$$

$$\frac{\partial^2 g_3(\bar{x})}{\partial x_3 \partial x_6} = \frac{\partial^2 g_3(\bar{x})}{\partial x_6 \partial x_3} = -.15$$

For  $g_4(\bar{x})$

$$\frac{\partial^2 g_4(\bar{x})}{\partial x_i^2} = 0 \quad \forall_i \quad \frac{\partial^2 g_5(\bar{x})}{\partial x_i \partial x_j} = 0 \quad \forall_{i,j}$$

For  $g_5(\bar{x})$

$$\frac{\partial^2 g_5(\bar{x})}{\partial x_i \partial x_j} = 0 \quad i=j; \quad i, j \neq 1, 7; \quad i=1, \dots, 8; \quad j=1, \dots, 8$$

$$\frac{\partial^2 g_5(\bar{x})}{\partial x_1 \partial x_7} = \frac{\partial^2 g_5(\bar{x})}{\partial x_7 \partial x_1} = -.15$$

For  $g_6(\bar{x})$

$$\frac{\partial^2 g_6(\bar{x})}{\partial x_1^2} = -.15 x_2^2 x_8 / (x_1^2 + x_2^2)^{\frac{3}{2}}$$

$$\frac{\partial^2 g_6(\bar{x})}{\partial x_1 \partial x_2} = \frac{\partial^2 g_6(\bar{x})}{\partial x_2 \partial x_1} = .15 x_1 x_2 x_8 / (x_1^2 + x_2^2)^{\frac{3}{2}}$$

$$\frac{\partial^2 g_6(\bar{x})}{\partial x_1 \partial x_8} = \frac{\partial^2 g_6(\bar{x})}{\partial x_8 \partial x_1} = -.15x_1 / (x_1^2 + x_2^2)^{\frac{1}{2}}$$

$$\frac{\partial^2 g_6(\bar{x})}{\partial x_2^2} = -.15x_1^2 x_8 / (x_1^2 + x_2^2)^{\frac{3}{2}}$$

$$\frac{\partial^2 g_6(\bar{x})}{\partial x_2 \partial x_8} = \frac{\partial^2 g_6(\bar{x})}{\partial x_8 \partial x_2} = -.15x_2 / (x_1^2 + x_2^2)^{\frac{1}{2}}$$

Any other partial derivative of  $g_6(\bar{x})$  does not indicate above has value equal to zero.

For  $g_7(\bar{x})$

$$\frac{\partial^2 g_7(\bar{x})}{\partial x_i \partial x_j} = x_4 x_5 x_6 x_7 x_8 / x_i x_j \quad i \neq j \quad i=4, \dots, 8; \quad j=4, \dots, 8$$

Any other partial derivative of  $g_7(\bar{x})$  does not indicated here has value equal to zero.

For  $g_h(\bar{x}) \quad h=8, 9, 10, 11, 12$

All partial derivatives have value equal to zero because they are linear constraints.

Follows a computer point out of FORTRAN subroutines RESNT, GRAD1 MATRIX and the actual output.



```

0001      SUBROUTINE GRAD111)
0002      IMPLICIT REAL*8(A-H,O-Z)
0003      COMMON/SHARE/X(100),DEL(100), A(100,100),N,M,NR,NP1,NM1
0004      DO 101 K=1,N
0005      101 DEL(K)=0.
0006      J = 1 + 1
0007      GU TO(1,2,3,4,5,6,7,8,9,10,11,12,13), J
0008      1 DO 19 K=1,3
0009      19 DEL(K)=-.05
0010      DO 20 K=4,8
0011      20 DEL(K)=-1./X(K)
0012      GO TO 14
0013      2 DEL(1) = .05-.15*X(4)
0014      DEL(4)=-.15*X(1)
0015      GO TO 14
0016      3 DEL(2) = .05-.15*X(5)
0017      DEL(5)=-.15*X(2)
0018      GO TO 14
0019      4 DEL(3) = .05-.15*X(6)
0020      DEL(6)=-.15*X(3)
0021      GO TO 14
0022      5 DEL(1)=-1
0023      GO TO 14
0024      6 DEL(1) = .05-.15*X(7)
0025      DEL(2)=-1.
0026      DEL(7)=-.15*X(1)
0027      GO TO 14
0028      7 Q =DSQRT(X(1)**2 +X(2)**2)
0029      DEL(1)= -.15*X(1)*X(8)/Q + .05
0030      DEL(2)= -.15*X(2)*X(8)/Q + .05
0031      DEL(3)=-1.
0032      DEL(8)=-.15*Q
0033      GO TO 14
0034      8 DO 80 K=4,8
0035      80 DEL(K)= X(4)*X(5)*X(6)*X(7)*X(8)/X(K)
0036      GO TO 14
0037      9 DEL(4)=-1.
0038      GO TO 14
0039      10 DEL(5)=-1.
0040      GO TO 14
0041      11 DEL(6)=-1.
0042      GO TO 14
0043      12 DEL(7)=-1.
0044      GO TO 14
0045      13 DEL(8)=-1.
0046      14 RETURN
0047      END

```

```
0022 SUBROUTINE MATRIX(I)
0023 IMPLICIT REAL*8(A-H,C-Z)
0024 COMMON/SHARE/ X(100),DEL(100), A(100,100),A,M,M,N,NPL,NML
0025 J = 1 +
0026 DO 100 K=1,N
0027 A(K,L) = 0.
0028 DO 100 L=1,N
0029 A(K,L) = 0.
0030 TO(1,2,3,4,5,6,7,8,9,9,9,9), J
0031 DO 11 L=4,6
0032 11 A(L,L) = 1./(A(L))**2
0033 DO 10 9
0034 2 A(1,4)=-.15
0035 DO 10 9
0036 3 A(2,5)=-.15
0037 DO 10 9
0038 4 A(3,6) = -.15
0039 DO 10 9
0040 5 A(1,7)=-.15
0041 DO 10 9
0042 7 8 =DSORT(X(11)**2 +X(2)**2)
0043 83 = 8**3
0044 A(1,1) = -.15*X(8)*X(2)**2/83
0045 A(1,2) = .15*X(1)*X(2)*X(8)/83
0046 A(1,8) = -.15*X(1)/8
0047 A(2,2) = -.15*X(8)*X(1)**2/83
0048 A(2,8) = -.15*X(2)/8
0049 DO 10 9
0050 3 DO 80 K=4,8
0051 DO 80 L=K,8
0052 IF(K.NE.L) A(K,L)=X(4)*X(5)*X(6)*X(7)*X(8)/(X(K)*X(L))
0053 30 CONTINUE
0054 9 RETURN
0055 END
```



APPARENTLY ROUND OFF ERRORS PREVENT A MORE ACCURATE DETERMINATION OF THE MINIMUM OF THIS SUBPROBLEM.

\*\*\*\*\*

POINT= 387      DOTT= 1.0101066D-04      RHO= 4.9649348D 01      MAGNITUDE= 4.4290387D-01      PHASE= 2  
 F= -9.5837030D 02      P= -6.6030639D 02      G= -1.2564342D 03      RSIGMA= 2.9806391D 02      H= 0.0  
 THE CURRENT VALUE OF X IS  
 6.9602250D 03      4.2457436D 03      7.9241784D 03      1.5432970D 00      1.8480071D 00      1.1494924D 00  
 1.5002834D 00      1.3099672D 00  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYIES  
 3.6757356D 01      3.5362703D 01      2.9891641D 01      3.9774986D 01      3.5921363D 01      3.4099943D 01  
 2.8707700D 00      2.4567030D 00      2.1519929D 00      2.8505076D 00      2.4997166D 00      2.6900328D 00

1ST ORDER ESTIMATES

F= -1.0192276D 03      P= -2.5591811D 03      G= -1.0138267D 03      RSIGMA= 0.0      H= 0.0  
 THE CURRENT VALUE OF X IS  
 7.3008622D 03      4.3508746D 03      8.7029537D 03      1.4782728D 00      1.8290790D 00      1.0034974D 00  
 1.3994248D 00      1.1722533D 00  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYIES  
 4.6143474D 01      2.3829924D 01      1.2513917D 02      -3.0086219D 02      -1.8382444D 01      -6.1481062D 02  
 2.7986934D-01      2.5217272D 00      2.1709210D 00      2.9965026D 00      2.6005752D 00      2.8277467D 00

LAGRANGE MULTIPLIERS

F= -1.0192276D 03      P= -2.5591811D 03      G= -1.0138267D 03      RSIGMA= 0.0      H= 0.0  
 THE CURRENT VALUE OF X IS  
 1.0248658D-06      2.7542664D-06      7.9068783D-07      2.0845607D 01      1.4538054D 01      3.7575201D 01  
 2.2058041D 01      2.8932950D 01  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYIES  
 3.6747265D-02      3.9702938D-02      5.5566626D-02      3.1382929D-02      3.8477596D-02      4.2697874D-02  
 6.024408D 00      8.2263697D 00      1.0720916D 01      6.1103931D 00      7.9456970D 00      6.8611733D 00  
 APPARENTLY ROUND OFF ERRORS PREVENT A MORE ACCURATE DETERMINATION OF THE MINIMUM OF THIS SUBPROBLEM.

\*\*\*\*\*

POINT=1630      DOTT= 1.5761148D-04      RHO= 1.2412337D 00      MAGNITUDE= 1.4343829D 00      PHASE= 2  
 F= -9.9516265D 02      P= -9.8257174D 02      G= -1.0077536D 03      RSIGMA= 1.2590911D 01      H= 0.0  
 THE CURRENT VALUE OF X IS  
 6.9940514D 03      4.5133009D 03      8.3687957D 03      1.5665527D 00      1.8024903D 00      1.1253714D 00  
 1.2684364D 00      9.6210441D-01  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYIES  
 6.2203031D 00      5.3880325D 00      5.7394406D 00      5.9486242D 00      5.6754961D 00      5.3087399D 00  
 3.0567066D-01      2.4334473D 00      2.1975097D 00      2.8746286D 00      2.7315636D 00      3.0378956D 00

2ND ORDER ESTIMATES

F= -1.0016149D 03      P= -1.0042221D 03      G= -1.0013771D 03      RSIGMA= 0.0      H= 0.0



THE CURRENT VALUE OF X IS  
 6.59270720 03 4.56900380 03 8.44587180 03 1.57329590 00 1.79304090 00 1.12385010 00  
 1.22041520 03 8.89709010-01  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYIES  
 -5.02749270-01 -4.11257510-01 -1.49030420 00 7.29977440 00 5.28560770-01 1.74442610 01  
 -1.25567480-01 2.42670410 00 2.20695910 00 2.87614990 00 2.77958180 00 3.11029100 00

# 1ST ORDER ESTIMATES

F= -1.00205670 03 P= -1.04309610 03 G= -1.00137710 03 RSIGMA= 0.0 H= 0.0

THE CURRENT VALUE OF X IS  
 7.00040430 03 4.56355060 03 8.45229890 03 1.57092030 00 1.79394190 00 1.12084130 00  
 1.22489340 00 8.96772610-01  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYIES  
 4.59543110-01 1.66030440-01 1.56230650 00 -4.04274790-01 2.57475430-01 1.81241900 00  
 -1.02639660-01 2.42987970 00 2.20605810 00 2.87915870 00 2.77510660 00 3.10322740 00

# LAGRANGE MULTIPLIERS

F= -1.00205670 03 P= -1.04309610 03 G= -1.00137710 03 RSIGMA= 0.0 H= 0.0

THE CURRENT VALUE OF X IS  
 2.55744080-08 6.09347420-08 1.77226080-08 5.05782200-01 3.82038970-01 9.80080580-01  
 7.71454540-01 1.34093940 00  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYIES  
 3.20797120-02 4.27556140-02 3.76803070-02 3.50769430-02 3.85341600-02 4.40423680-02  
 1.32545250 01 2.09608870-01 2.57034830-01 1.50206970-01 1.66353100-01 1.34495540-01  
 APPARENTLY ROUND OFF ERRORS PREVENT A MORE ACCURATE DETERMINATION OF THE MINIMUM OF THIS SUBPROBLEM.

\*\*\*\*\*

POINT=1742 DOTT= 1.21899020-04 RHD= 3.10308420-02 MAGNITUDE= 3.92355380 00 PHASE= 2

F= -9.99838320 02 P= -9.98800140 02 G= -1.00087750 03 RSIGMA= 1.03867860 00 H= 0.0

THE CURRENT VALUE OF X IS  
 6.59996630 03 4.55767180 03 8.41431120 03 1.57063240 00 1.79479040 00 1.12489290 00  
 1.23003630 00 9.28035240-01  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYIES  
 1.00956180 00 8.73916710-01 9.35933290-01 9.33692570-01 9.13825670-01 8.54963650-01  
 4.74812290-02 2.42936760 00 2.20520960 00 2.87510710 00 2.76996170 00 3.07196480 00

# 2ND ORDER ESTIMATES

F= -1.00064240 03 P= -1.00079030 03 G= -1.00070120 03 RSIGMA= 0.0 H= 0.0

THE CURRENT VALUE OF X IS  
 6.59994800 03 4.56606790 03 8.42210460 03 1.57141080 00 1.79332900 00 1.12490460 00  
 1.22277360 00 9.22274280-01  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYIES  
 1.42637370-02 3.42686390-02 -4.19422600-03 1.99958410-03 2.00452920-02 3.29422920-03  
 2.06162190-03 2.42658920 00 2.20667100 00 2.87509540 00 2.77722620 00 3.07772570 00

## 1ST ORDER ESTIMATES

F= -1.0007158D 03 P= -1.0018430D 03 G= -1.0007012D 03 RSIGMA= 0.0 H= 0.0

THE CURRENT VALUE OF X IS  
 7.0000382D 03 4.5660050D 03 8.4228595D 03 1.5713985D 00 1.7933443D 00 1.1248030D 00  
 1.2228268D 00 9.2163673D-01

THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITIES  
 3.0252493D-02 3.7557043D-02 3.4519712D-02 -8.1572752D-03 2.5984194D-02 4.8619921D-02  
 2.5193290D-05 2.4266015D 00 2.2066557D 00 2.8751970D 00 2.7771732D 00 3.0783633D 00

## LAGRANGE MULTIPLIERS

F= -1.0007168D 03 P= -1.0018480D 03 G= -1.0007012D 03 RSIGMA= 0.0 H= 0.0

THE CURRENT VALUE OF X IS  
 6.3345147D-10 1.4938517D-09 4.3828481D-10 1.2578953D-02 9.6331001D-03 2.4522866D-02  
 2.0509559D-02 3.6030031D-02

THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITIES  
 3.0445825D-02 4.0630623D-02 3.5424503D-02 3.5594735D-02 3.7159243D-02 4.2452011D-02  
 1.3764158D 01 5.2578365D-03 6.3810747D-03 3.7539243D-03 4.0443248D-03 3.2882218D-03

APPARENTLY ROUND-OFF ERRORS PREVENT A MORE ACCURATE DETERMINATION OF THE MINIMUM OF THIS SUBPROBLEM.

\*\*\*\*\*

POINT=1844 DOTT= 1.2102176D-04 RHO= 7.7577106D-04 MAGNITUDE= 1.8096461D 00 PHASE= 2

F= -1.0005912D 03 P= -1.0004438D 03 G= -1.0007185D 03 RSIGMA= 1.3733936D-01 H= 0.0

THE CURRENT VALUE OF X IS  
 6.9998568D 03 4.5643866D 03 8.4218738D 03 1.5712984D 00 1.7937143D 00 1.1248035D 00  
 1.2242877D 00 9.2240364D-01

THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITIES  
 1.6350773D-01 1.3868661D-01 1.5095115D-01 1.4322202D-01 1.3067106D-01 1.2423937D-01  
 7.7809781D-03 2.4287016D 00 2.2062857D 00 2.8751965D 00 2.7757123D 00 3.0775964D 00

## 2ND ORDER ESTIMATES

F= -1.0007207D 03 P= -1.0007245D 03 G= -1.0007144D 03 RSIGMA= 0.0 H= 0.0

THE CURRENT VALUE OF X IS  
 7.0000052D 03 4.5656385D 03 8.4233053D 03 1.5714241D 00 1.7935165D 00 1.1247863D 00  
 1.2232174D 00 9.2133852D-01

THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITIES  
 3.9355305D-03 -9.5589533D-05 2.7528389D-03 -5.1606359D-03 -1.7343593D-02 -1.3791982D-02  
 3.5814249D-04 2.4265759D 00 2.2064835D 00 2.8752137D 00 2.7767826D 00 3.0786615D 00

## 1ST ORDER ESTIMATES

F= -1.0007206D 03 P= -1.0007525D 03 G= -1.0007144D 03 RSIGMA= 0.0 H= 0.0

THE CURRENT VALUE OF X IS

7.00000000 03 4.56564770 03 8.42329410 03 1.57142350 00 1.79351220 00 1.12478670 00  
 1.22324570 00 9.21345980-01  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYS  
 4.56564770-03 8.45495410-04 3.54698340-03 -5.23555190-03 -1.62604030-02 -1.22314450-02  
 3.44524300-04 2.42857250 00 2.20643780 00 2.87521330 00 2.77679230 00 3.07865400 00

# LAGRANGE MULTIPLIERS

F= -1.00072060 03 P= -1.00075250 03 G= -1.00071440 03 RSIGMA= 0.0 H= 0.0  
 THE CURRENT VALUE OF X IS  
 1.58327100-11 3.72364890-11 1.09374510-11 3.14207270-04 2.41116560-04 6.13169120-04  
 5.17567050-04 9.11783130-04  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYS  
 2.49172990-02 4.03333720-02 3.40455770-02 3.7d193440-02 4.54333490-02 5.02591470-02  
 1.24134400 01 1.31516020-04 1.59371260-04 9.38422700-05 1.00689610-04 8.19049700-05  
 APPARENTLY ROUND-OFF ERRORS PREVENT A MORE ACCURATE DETERMINATION OF THE MINIMUM OF THIS SUBPROBLEM.

\*\*\*\*\*

POINT=1922 DOTT= 5.72030410-05 RHG= 1.93942760-05 MAGNITUDE= 2.14420920 00 PHASE= 2  
 F= -1.00070090 03 P= -1.00068040 03 G= -1.00072140 03 RSIGMA= 2.05011150-02 H= 0.0  
 THE CURRENT VALUE OF X IS  
 6.79997770 03 4.56567570 03 8.42299510 03 1.57140710 00 1.79350380 00 1.12479810 00  
 1.22324560 00 9.21562650-01  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYS  
 2.69034830-02 2.23736430-02 2.46567310-02 2.22467420-02 1.94206780-02 1.87725930-02  
 1.24347630-03 2.42859240 00 2.20649620 00 2.87520190 00 2.77675420 00 3.07843730 00

# 2ND ORDER ESTIMATES

F= -1.00072350 03 P= -1.00072420 03 G= -1.00072150 03 RSIGMA= 0.0 H= 0.0  
 THE CURRENT VALUE OF X IS  
 7.00000000 03 4.56560290 03 8.42320350 03 1.57142760 00 1.79346300 00 1.12479730 00  
 1.22324600 00 9.21406210-01  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYS  
 1.19172750-03 5.29519400-04 8.70789250-04 -3.02693120-04 -1.08967550-03 -7.27926560-04  
 5.65413800-05 2.42857240 00 2.20653700 00 2.87520270 00 2.77695400 00 3.07859380 00

# 1ST ORDER ESTIMATES

F= -1.00072340 03 P= -1.00072490 03 G= -1.00072150 03 RSIGMA= 0.0 H= 0.0  
 THE CURRENT VALUE OF X IS  
 7.00000040 03 4.56579900 03 8.42320570 03 1.57142750 00 1.79346420 00 1.12479710 00  
 1.22305010 00 9.21404710-01  
 THE CONSTRAINT VALUES  
 NOT INCLUDING THE NON-NEGATIVITYS  
 1.24752070-03 5.37390500-04 9.37690570-04 -4.26004840-04 -1.46894070-03 -1.01549320-03  
 6.38742430-05 2.42857250 00 2.20653580 00 2.87520290 00 2.77694990 00 3.07859530 00

LAGRANGE MULTIPLIERS

F = -1.00072340 03      P = -1.00072490 03      G = -1.00072150 03      RSIGMA = 0.0      H = 0.0

THE CURRENT VALUE OF X IS

3.95804080-13	9.30427390-13	2.73363470-13	7.85409500-06	6.02932910-06	1.53293750-05
1.29612250-05	2.29362010-05				

THE CONSTRAINT VALUES

NOT INCLUDING THE NON-NEGATIVITIES

2.67951720-02	3.87436020-02	3.19008740-02	3.90463470-02	5.14215070-02	5.50332350-02
1.17732900 01	3.29824430-06	3.98352190-06	2.34604790-06	2.51535160-06	2.04650560-06

## 11. APPENDIX C: GEOMETRIC PROGRAMMING, COMPUTER OUTPUT



```

X( 6)=      0.50000000
X( 7)=      0.50000000

INITIAL VALUE OF PRIMAL OBJECTIVE FUNCTION      3.01708817E+00

INITIAL VALUE OF PRIMAL CONSTRAINTS
G( 0)=      3.01708817
G( 1)=      0.79244660
G( 2)=      0.93969515
G( 3)=      0.75000000
G( 4)=      0.62500000
G( 5)=      1.00000000
G( 6)=      0.30170882
G( 7)=      0.03314454

INITIAL VALUES OF DUAL MULTIPLIERS
TAU( 0) =      -0.10429218
TAU( 1) =      -2.30258509
TAU( 2) =      0.69314718
TAU( 3) =      0.87546874
TAU( 4) =      2.30258509
TAU( 5) =      1.60943791
TAU( 6) =      -0.69314718
TAU( 7) =      -0.69314718
TAU( 8) =      1.00000000
TAU( 9) =      1.00000000
TAU(10) =      1.00000000
TAU(11) =      1.00000000
TAU(12) =      1.00000000
TAU(13) =      1.00000000
TAU(14) =      1.00000000

```

ITERATION NUMBER 1	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	3.01708817
APPROX. VALUE OF DUAL OBJECT. FUNCT.	1.03944118
ITERATION NUMBER 2	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	3.01708817
APPROX. VALUE OF DUAL OBJECT. FUNCT.	1.45251498
ITERATION NUMBER 3	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	1.74315055
APPROX. VALUE OF DUAL OBJECT. FUNCT.	1.44241147
ITERATION NUMBER 4	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.89006593
APPROX. VALUE OF DUAL OBJECT. FUNCT.	1.39348441
ITERATION NUMBER 5	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.62275919
APPROX. VALUE OF DUAL OBJECT. FUNCT.	1.24337966
ITERATION NUMBER 6	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.56240067
APPROX. VALUE OF DUAL OBJECT. FUNCT.	1.03336320
ITERATION NUMBER 7	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.40845325
APPROX. VALUE OF DUAL OBJECT. FUNCT.	0.55947341
ITERATION NUMBER 8	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.36629719
APPROX. VALUE OF DUAL OBJECT. FUNCT.	0.38789633
ITERATION NUMBER 9	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.36745176
APPROX. VALUE OF DUAL OBJECT. FUNCT.	0.36517971
ITERATION NUMBER 10	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.36773917
APPROX. VALUE OF DUAL OBJECT. FUNCT.	0.36742131
ITERATION NUMBER 11	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.36773076
APPROX. VALUE OF DUAL OBJECT. FUNCT.	0.36772666
ITERATION NUMBER 12	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.36773073
APPROX. VALUE OF DUAL OBJECT. FUNCT.	0.36772619
ITERATION NUMBER 13	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.36773073
APPROX. VALUE OF DUAL OBJECT. FUNCT.	0.36772905
ITERATION NUMBER 14	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.36773073
APPROX. VALUE OF DUAL OBJECT. FUNCT.	0.36773011
ITERATION NUMBER 15	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.36773073



APPROX. VALUE OF DUAL OBJECT. FUNCT.	0.36773051
ITERATION NUMBER 16	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.36773073
APPROX. VALUE OF DUAL OBJECT. FUNCT.	0.36773065
ITERATION NUMBER 17	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.36773073
APPROX. VALUE OF DUAL OBJECT. FUNCT.	0.36773070
ITERATION NUMBER 18	
APPROX. VALUE OF PRIMAL OBJECT. FUNCT.	0.36773073
APPROX. VALUE OF DUAL OBJECT. FUNCT.	0.36773072
CONSTRAINTS TIGHT - OPTIMAL SOLN	

# DUAL CONSTRAINT INFEASIBILITY

0	-2.22044605E-16
1	1.84845548E-08
2	1.23230365E-08
3	1.38777878E-16
4	-2.63677968E-16
5	-8.32667268E-17
6	-7.54604712E-17
7	-3.19189120E-16
8	2.49800181E-16
9	0.00000000E+00
10	-2.22044605E-16
11	1.38777878E-17
12	-2.77555756E-17
13	-6.07553430E-08
14	-8.86912807E-08

## OPTIMAL VALUES OF DUAL VARIABLES

### A. VARIABLES FOR PRIMAL OBJECT. FUNCT.

1	1.00000000E+00
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### B. VARIABLES FOR INEQUAL CONSTS.

INEQUALITY CONSTRAINT NUMBER 1	
1	6.00000000E-01
2	3.10586583E-01
DEL( 1,0)=	9.10586583E-01

INEQUALITY CONSTRAINT NUMBER 2	
1	4.00000000E-01
DEL( 2,0)=	4.00000000E-01

INEQUALITY CONSTRAINT NUMBER 3	
1	7.28469266E-01
2	3.60000000E-01
DEL( 3,0)=	1.08846927E+00

INEQUALITY CONSTRAINT NUMBER 4	
1	3.10586583E-01
DEL( 4,0)=	3.10586583E-01

INEQUALITY CONSTRAINT NUMBER 5	
1	4.00000000E-02
2	1.82117317E-01
DEL( 5,0)=	2.22117317E-01

INEQUALITY CONSTRAINT NUMRER 6	
1	2.31945414E-09
DEL( 6,0)=	6.30747972E-08

INEQUALITY CONSTRAINT NUMBER 7	
1	3.31270451E-08
DEL( 7,0)=	1.21818326E-07

VALUES OF DUAL MULTIPLIERS

TAU( 0)=	2.00040431E+00
TAU( 1)=	1.06393205E+00
TAU( 2)=	9.05112707E-01
TAU( 3)=	4.05465108E-01
TAU( 4)=	2.09955750E+00
TAU( 5)=	2.91048772E+00
TAU( 6)=	-1.71432624E+00
TAU( 7)=	-1.98554619E-01
TAU( 8)=	-9.06333710E-01
TAU( 9)=	-8.37092681E-02
TAU(10)=	-1.08477237E+00
TAU(11)=	1.69292566E-01
TAU(12)=	5.04549584E-01
TAU(13)=	1.55789446E+01
TAU(14)=	1.49207350E+01

VALUES OF OPTIMAL PRIMAL VARIABLES

X( 1) =	2.89774269
X( 2) =	2.47221054
X( 3) =	1.50000000
X( 4) =	8.16255722
X( 5) =	18.36575373
X( 6) =	0.18008501
X( 7) =	0.81991499

OPTIMAL VALUE OF PRIMAL OBJECTIVE FUNCTION      3.67730733E-01

OPTIMAL VALUE OF DUAL OBJECTIVE FUNCTION      3.67730721E-01